The impact of digital transformation on firm's export : Mechanism, performance and behaviour

The Impact of Digital Transformation on Firms' Export: Mechanism, Performance and Behaviour

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Abstract

This thesis explores how digital transformation affects firms' exporting activities through three interrelated studies. Each study concentrates on a different but connected aspect: the underlying mechanisms that influence exports, the resulting changes in export performance, and the shifts in firms' export behaviours. The research integrates theoretical modelling and empirical analysis, and comprehensively explains how digital transformation reshapes firms' operational dynamics in international trade.

In the first study, a general equilibrium model is developed to analyse how digital transformation affects firms' capital and labour efficiencies, subsequently influencing their production costs and profitability. This theoretical framework bridges a gap by detailing how digital transformation impacts export performance and profits. Simulation analyses reveal that while digital transformation generally enhances firm profits, the optimal transformation strategy is not universal and is based on market competition. In low-competition markets, excessive digital transformation may not be advantageous, whereas in highly competitive markets, a moderate level of digital transformation could be the least favourable strategy.

The second study of the thesis introduces a novel measurement method for digital transformation based on text analysis of firm-level data. The empirical research employs the Firm-Specific Advantages (FSAs) theory and an extended heterogeneous firm model. The results demonstrate a significant positive effect of digital transformation on export performance, primarily through improvements in capital and labour efficiencies. Mediation tests indicate that capital efficiency serves as a robust mechanism, while labour efficiency's impact is more pronounced in firms with initially low labour efficiency. Furthermore, when there is an imbalance in the development of capital and labour efficiencies, directing digital transformation efforts toward the weaker efficiency yields more significant benefits, supporting the optimal transformation allocation theory proposed earlier.

The last study separately distinguishes between management and production digital transformations to examine their effects on firms' export diversification and concentration.

Empirical findings show that management digital transformation significantly increases export diversification while reducing export concentration. In contrast, production digital transformation enhances export diversification but has no significant effect on export concentration. These results suggest that different types of digital transformation act as unique resources influencing firms' export behaviours differently. The study underscores the importance for firms to select digital transformation pathways that align with their specific needs and for policymakers to guide the direction of digital transformation, thereby effectively shaping firms' export strategies.

This thesis contributes to the literature by integrating theoretical and empirical analyses to elucidate how digital transformation affects firms' export performance and behaviours. It highlights the necessity of balanced efficiency improvements and tailored digital transformation approaches, providing practical insights for firms aiming to maximise benefits in the global market. The findings offer valuable implications for corporate decision-makers and policymakers in enhancing global competitiveness through strategic digital transformation.

Keywords: Digital Transformation; Production Digital Transformation; Management Digital Transformation; Capital Efficiency; Labour Efficiency; Export Performance; Export Diversification; Export Concentration; General Equilibrium Model; Firm-Specific Advantages; Resource-Based View.

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Chapter 1: Introduction

1.1. Research Background and Questions

Over the past decade, digital transformation has attracted increasing attention from both academia and industry, leading to explosive growth in related research (Denicolai et al., 2021; Hanelt et al., 2021; F. Wang & Ye, 2023). As discussions deepen, scholars have begun to focus on measuring digital transformation and examining its impact on firms as well as the economic environment (Bertello et al., 2021; Denicolai et al., 2021; George et al., 2021; Verhoef et al., 2021). Some have also expressed concerns about whether digital transformation can deliver the expected returns to companies (Feliciano-Cestero et al., 2023; Weill & Woerner, 2018). Within the scope of international business, another essential topic worthy of exploration is how digital transformation affects firms' exports (AL-Khatib, 2023; B. Zhang et al., 2024). Exporting is a crucial activity for companies in open economies, directly influencing operational performance indicators such as profits and market share. As a multidimensional change within organizations, digital transformation inevitably impacts their export behaviours and performance (Akerman, 2018; Bernard et al., 2007, 2012).

Globally, a vast number of enterprises are promoting digital transformation to varying degrees, whether spontaneously or in response to external pressures (Ferreras-Méndez et al., 2019; Gaigné et al., 2018). Some companies emphasise upgrading production equipment or management resources to enhance manufacturing efficiency (Erbahar & Rebeyrol, 2022; Soto-Acosta et al., 2016; Tien Dzung, 2022), while others prioritise training or hiring sophisticated workers to achieve higher labour productivity (Cieślik et al., 2023; Ganguly & Acharyya, 2021; Karavidas, 2020; Marchal & Šerić, 2017). However, many firms adopt digital transformation merely to follow trends without understanding their internal motivations and necessities. Consequently, there is a growing interest in comprehending the underlying mechanisms of digital transformation and its actual impact on firms, aiming to help them implement it more effectively (F. Li et al., 2016; W. Li & Li, 2022; Petropoulou, 2010).

As reviewed by Vial, current research on digital transformation can be divided into micro and macro dimensions (Vial, 2019). From a micro perspective, academic studies primarily focus on how to measure digital transformation and how it affects firms' operational performance (Abeliansky & Hilbert, 2017; F. Wang & Ye, 2023; Yue, 2023), including sales volumes, profits, and shareholder returns in the stock market (Westerman et al., 2011). From a macro perspective, research is more concerned with its impact on employment, wage levels, local development, and social responsibility (Acemoglu & Restrepo, 2018b, 2018a; Dinlersoz & Wolf, 2023; Yue, 2023). Although scholars have endeavoured to study the effects of digital transformation at various levels, these studies have consistently overlooked its role in firms' exports, an essential topic in an open economy (F. Wang et al., 2023; F. Wang & Ye, 2023). Consequently, there remains a significant gap in research on how digital transformation affects firms' export performance.

Potential research topics related to digital transformation and firm exports can be explored in two directions. Firstly, building a theoretical model that incorporates digital transformation to simulate the production process and clarify internal mechanisms is essential (Gong & Ribiere, 2021; Kraus et al., 2021; Zhai et al., 2022). However, due to the inherent complexity of digital transformation, few studies have systematically discussed how it affects a firm's performance from an internal perspective (Vial, 2019). In previous theoretical research, digital transformation has not been distinguished from traditional technological progress; it is often regarded as an assigned exogenous variable that does not change with firms' decisions (Clemente-Almendros et al., 2024). As noted in the literature, digital transformation is not merely a simple technological advancement but a comprehensive reform encompassing production, management, and human resources (Song, 2024; Wessel et al., 2021). Therefore, at the theoretical level, previous models can no longer adequately capture the nuances of current digital transformation (Baiyere et al., 2023). Firms should consider the costs and benefits of digital transformation; thus, whether to adopt it and to what extent should be treated as an endogenous decision made by the firms themselves.

Beyond theoretical modelling, empirical approaches can also fill the research gap. A primary issue that mainstream studies attempt to address is the measurement of digital transformation (Vial, 2019; F. Wang et al., 2023; F. Wang & Ye, 2023; Warner & Wäger, 2019). The degree of a firm's digital transformation is primarily measured using methods such as dummy variables, city or regional proxy variables (Abeliansky & Hilbert, 2017; Combes et al., 2012), and text analysis (Hoberg & Maksimovic, 2014; Mehl, 2006; F. Wang et al., 2023). Each of these methods balances accuracy and complexity. However, even relatively sophisticated text analysis methods, such as calculating word frequencies, struggle to achieve significant breakthroughs in accurately measuring digital transformation (Wu et al., 2022). Additionally, academic studies discuss the impact of digital transformation on firms and its subsequent economic consequences (Acemoglu

& Restrepo, 2018a; W. Li & Li, 2022; Verhoef et al., 2021). The focus is mainly on firms' profits, profitability, and stock price changes, while the crucial aspect of firms' export performance lacks detailed research (Llopis-Albert et al., 2021). Some studies have only found correlations between variables rather than establishing causal relationships (Ouma & Premchander, 2022). This underscores the need to identify the internal mechanisms by which digital transformation affects firms.

Another topic often mentioned but insufficiently explored in the literature is the direction of firms' digital transformation and its impact on export behaviours (Alsheibani et al., 2018). Since every enterprise is unique, firms pursue digital transformation with diverse motivations and employ tailored strategies to implement it (Camodeca & Almici, 2021; L. Zhang et al., 2022). However, academic research often uses a single standard to measure digital transformation across different industries, which inevitably overlooks inter-firm differences (Gong & Ribiere, 2021). For instance, disparities in the degree of digital transformation between companies cannot be simply measured by the number of automated robots or the prevalence of data analysis systems within the enterprise (Nadkarni & Prügl, 2021). Therefore, developing a more detailed measurement method for firms' digital transformation is essential.

Moreover, firms' export behaviour differs from export performance, focusing more on their export preferences. At the micro level, a firm's export preferences are reflected in its entry and exit behaviours in overseas markets (Impullitti et al., 2013; Melitz, 2003). At the macro level, these behaviours aggregate to form a country's export pattern (Haddoud et al., 2021). These indicators are crucial in discussions of international trade and understanding how these preferences change under the influence of digital transformation is equally important.

In summary, there are three main research gaps in the existing literature on digital transformation and firms' exports. First, theoretical models that explain the internal mechanisms linking digital transformation to firms' exports remain underdeveloped. Second, measuring the degree of digital transformation accurately poses a challenge, thereby constraining empirical investigations into its effect on export performance. Third, there is limited discussion on how different directions of digital transformation shape firms' export behaviours. Therefore, this doctoral thesis aims to address the following research questions through one theoretical study and two empirical studies:

1. What is the theoretical model that describes the mechanism of how digital transformation affects firms' exports?
2. How can the degree of digital transformation be measured accurately, and what empirical evidence links this measurement to firms' export performance?
3. How do different directions of digital transformation shape firms' export behaviours?

1.2. Research Objectives and Potential Contributions

The general objective of this thesis is to explore how digital transformation affects firms in the context of export activities. This overarching aim is divided into three components: understanding the internal mechanisms, assessing the impact on performance, and examining changes in export preferences.

The first study addresses the initial research question by constructing a theoretical model of firm production that integrates digital transformation as an endogenous variable. This incorporation allows for a comprehensive exploration of how digital transformation influences firms' production efficiency, subsequently affecting costs, profits, and export volumes. By calibrating the model parameters and conducting simulations, the study examines the effects of digital transformation on firms operating under different competitive market environments. The research aims to unveil the internal mechanisms through which digital transformation impacts firms' exports by employing a dynamic general equilibrium model. In this model, the decisions to implement digital transformation and the extent of its adoption are determined endogenously. Additionally, the study seeks to identify the optimal levels of digital transformation for firms across various market conditions, providing analytical frameworks and insights valuable to both academia and industry practitioners.

The second study aims to develop an accurate method for measuring the extent of digital transformation, enabling a more precise analysis of its impact on firms' export performance. To achieve this, a TF-IDF weighted text analysis approach is employed, offering a significant improvement over traditional measurement technique. This refined method allows for a more detailed assessment of the interactions between firms' digital transformation and export performance. The potential contributions of this study include the development of a text-based measurement method for firms' digital transformation and the provision of empirical evidence regarding its impact on export performance.

The third study focuses on the directions of digital transformation among firms and the resultant changes in export behaviour. Firstly, in order to identify different directions of digital transformation, a modification was applied to the measurement method developed in the second study. Then, the third study investigates how different directions of digital transformation influence firms' export behaviours in different ways. The potential contributions of this study are threefold: first, it could make the measurement method developed in study two capable of identifying the specific directions of firms' digital transformation. Second, it could construct two indicators to measure firms' export behaviours: export concentration and export diversification. Third, if the relationships between different directions of digital transformation and export behaviours are recognised, there could be practical guidance for firms and policymakers on choosing digital transformation paths to enhance global competitiveness. These indicators facilitate the examination of export behaviours from multiple dimensions, offering exploratory insights for future research in international trade and digital transformation.

1.3. Structure of the Thesis

This thesis is structured into five chapters. The current chapter introduces the background and outlines the research content of the entire doctoral thesis. Chapters 2, 3, and 4 consist of three independent research studies that address the aforementioned research questions. Specifically, Chapter 2 presents the first study, which, from a theoretical perspective, develops a general equilibrium model to investigate the mechanisms of digital transformation that affect firms' production processes, thereby influencing their exports. In Chapter 3, the measurement method of digital transformation is developed, and empirical methods are employed to verify the impact of digital transformation on firms' export performance. In Chapter 4, multiple directions of digital transformation are identified, and how they influence firms' export behaviours is empirically examined. Finally, Chapter 5 summarizes the entire research, providing discussions and policy recommendations based on the results. The structure of the three studies is shown in Figure 1.

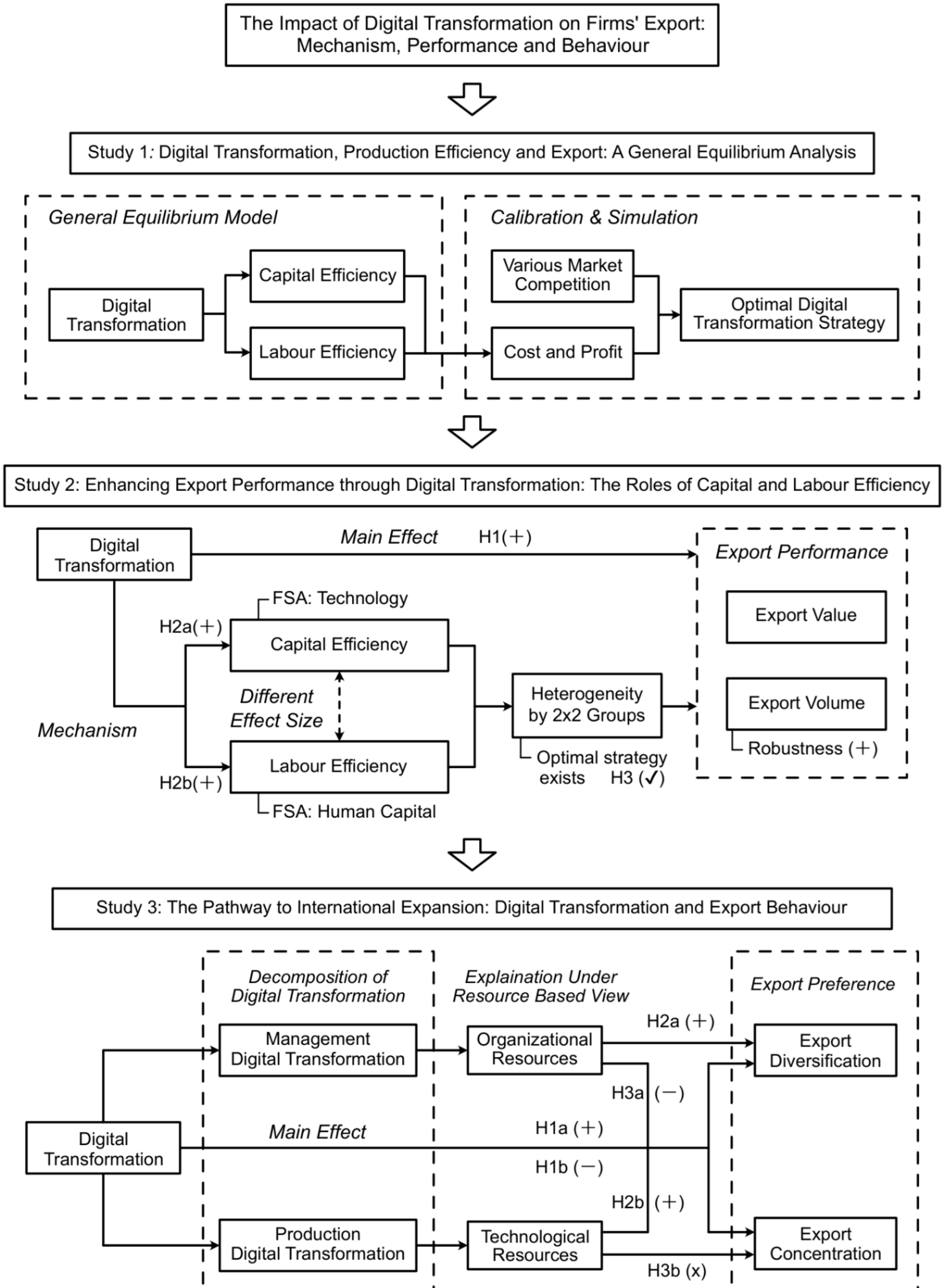


Figure 1. The structure of the three studies

Chapter 2: Digital Transformation, Production Efficiency and Export: A General Equilibrium Analysis

Abstract

This paper analyses the impacts of digital transformation on production efficiencies and export strategies within a general equilibrium framework. It explores how digital transformation reshapes firms' capital and labour efficiencies, influencing their production strategies and profitability. The study bridges a theoretical gap by offering a detailed model of how digital transformation affects export performance and profits. Then this paper provided an empirical exploration of its differential impacts on capital and labour efficiencies, highlighting optimal input ratios. Finally, this paper provided a simulation analysis of digital strategy optimization in varying competitive export markets. Findings suggest that digital transformation generally boosts firm profits, but a one-size-fits-all approach is suboptimal. In low-competition markets, excessive digitalization may not be beneficial, whereas in high-competition markets, a medium level of digital transformation could be the least favourable.

Keywords: Digital Transformation; General Equilibrium; Export Strategies; Production Efficiencies; Market Competition.

2.1. Introduction

Over the past two decades, there has been a rapid development in the digital economy (Feliciano-Cestero et al., 2023). Firms apply digital technologies such as autonomous robotics (Acemoglu & Restrepo, 2018b), the internet of things (Warner & Wäger, 2019), digital embedded system (Fürstenau et al., 2019), big data (AL-Khatib, 2023; Lu, 2020), and artificial intelligence (Denicolai et al., 2021). The series of actions undertaken by firms are generally referred to as digital transformation (Hanelt et al., 2021; Rolland et al., 2018; Vial, 2019). Unlike the conventional literature that discusses IT-enabled organizational transformation, digital transformation emphasises a more profound reshaping of the entire operation patterns and economic models of businesses (Baiyere et al., 2023; Song, 2024; Wessel et al., 2021).

There is a vast body of existing literature discussing the impacts of digital transformation from various scopes. At the micro level, studies have covered the effects of digital transformation on business performance metrics, such as sales and profits (Brynjolfsson et al., 2019; Cong et al., 2024; Llopis-Albert et al., 2021), stock market performance (Wu et al., 2022), moral hazard problem (M. Liu et al., 2021), advertise strategy (Dukes & Liu, 2024; Song, 2024) and innovation capacity (Ansari et al., 2016; Lemon & Verhoef, 2016). In contrast, at the macro level, these studies primarily focus on the implications of digital transformation on local economic growth, employment, wage levels, and social welfare (Acemoglu & Restrepo, 2018b; Baldwin & Robert-Nicoud, 2005; Berlingieri et al., 2018).

However, the effects of digital transformation are not confined to the domestic operations of a firm. They extend to the firm’s international operations as well, particularly its export performance (Bharadwaj et al., 2013). A firm’s export performance is a critical determinant of its global competitiveness and economic viability (J. Chen et al., 2016). It not only contributes to the firm’s profitability but also enables it to leverage international markets for growth and diversification (Qian & Mahmut, 2016). In the era of digitalization, understanding the effects of digital transformation on a firm’s export performance is of paramount importance. It provides insights into how firms can harness digital technologies to enhance their export capabilities, thereby driving their global success and contributing to economic development (Elia et al., 2021).

In the domain of export-related studies, early works have established fundamental and practical theoretical frameworks (Krugman, 1979, 1980; Melitz, 2003). Particularly, the heterogeneity model of firms proposed by Melitz paved the way for a significant branch in the study of firm exports (Melitz, 2003). This model has since been extended in various ways (Bastos & Silva, 2010; Combes et al., 2012), to include the impacts of technological advancements on productivity, and consequently on firms' producing and exporting behaviour (Acemoglu & Restrepo, 2018a; C. S. A. Cheng et al., 2020; Deng et al., 2022; Filatotchev et al., 2009; Melitz & Redding, 2021).

In addition to this, it is crucial to acknowledge that digital transformation should not be viewed as an exogenous efficiency enhancement, as the manner technological progress is often perceived in the existing literature (Dinlersoz & Wolf, 2023). Rather, it constitutes a complex process that requires firms to carefully and sensibly weigh the pros and cons and make informed decisions (Hanelt et al., 2021). For instance, the implementation of digital production lines and internet of things (IoT) technologies requires not only substantial capital investment for purchasing the necessary equipment, but also the allocation of higher wages for the recruitment or training of staff who can proficiently utilise these technologies (Correani et al., 2020; Gebauer et al., 2020). Moreover, the management costs associated with the newly digitalized equipment further add to the burden of digital transformation (Weill & Woerner, 2018).

Taking these factors into consideration, digital transformation process, while predominantly beneficial as reported in the literature (Feliciano-Cestero et al., 2023), is not without its drawbacks. In the wave of digital transformation, not every firm reaps the benefits (W. Li & Li, 2022). Firms must not solely focus on potential gains but also consider the hidden costs associated with it. It has been reported that digital transformation initiatives primarily aimed at enhancing operational efficiency experience an alarmingly high failure rate, with about 90% of such finally not delivering the expected outcomes (Ramesh & Delen, 2021). Such high failure rates can have detrimental consequences on a firm's overall functioning and can suppress its enthusiasm for future innovative pursuits (Davenport & Westerman, 2018; Ramesh & Delen, 2021).

Therefore, it is an oversimplification to equate digital transformation to an exogenous elevation in technological growth (Baiyere et al., 2023). It is, instead, a decision permeated with potential risks and uncertainties (Atkeson & Burstein, 2010; Bustos, 2011). This underscores the inadequacy of the traditional literature's approach of incorporating technology development as an exogenous parameter in modelling the relationship between digital transformation and export performance (Melitz & Redding, 2014). Consequently, this highlights the pressing need for theoretical models that consider digital transformation in firm's operating strategies (Viard & Economides, 2015).

Here, this paper identifies a gap in the existing literature where theoretical articles related to firm exports have not sufficiently recognized the uniqueness of digital transformation. These studies also fail to capture the fact that digital transformation should be treated as an endogenous strategy rather than an exogeneous technology improvement (Matt et al., 2015; Parviainen et al., 2017; Verhoef et al., 2021). Thus, the existing literature is unable to extensively investigate how digital transformation specifically impacts the production and management process of firms and consequently influences their operating strategy and export performance. The need to address this gap presents an opportunity for further exploration and nuanced understanding in this domain.

Therefore, based on the classical theory of firm heterogeneity in exports, this paper focuses on conceptualizing digital transformation as a continuous endogenous variable within firms. It analyses the impact on export performance and the underlying mechanisms driving this relationship. Finally, through parameter calibration and simulation, the discussion extends to the optimal strategies for firms in environments with various levels of market competition.

2.2. The Model

To provide a nuanced understanding of the effects of digital transformation on firms' export performance, this paper developed a comprehensive general equilibrium model in this section. The general equilibrium model in this chapter ensures that all relevant markets (labour market and final goods market) are cleared simultaneously. In other words, in addition to modelling the firm's production and export decision, the consumers' utility maximization and the equilibrium price level are incorporated explicitly, ensuring that input prices and output prices are determined endogenously. This allows the model to capture how changes in production efficiency and digital transformation affect not only the firm's costs and output, but also the aggregate demand and resource allocation across the whole economy.

The setting of the model is rooted in Melitz's framework for heterogeneous firm export behaviour (Melitz, 2003). This section tries to explicitly incorporate the impacts of digital transformation on both business operations and production processes, then exploring the multidimensional effects of digital transformation on firms. Subsequently, this section also makes a detailed discussion of the customer demand, the production function, and cost structures of the firms in the market.

2.2.1. The role of Digital Transformation

Digital transformation plays a pivotal role across various aspects of business production, from the integration of digital technologies in areas such as the internet of things (IoT), to efficient data transmission and intelligent inventory management (Vial, 2019). In real-world operations, every production factor, including but not limited to labour and capital, is affected by digital transformation (J. Lee & Berente, 2012). For analytical generality under the context of this section, it is assumed that the key inputs in the production of goods are labour and capital. According to the theoretical framework of heterogeneous firms model (Melitz, 2003), the key variable under consideration is the efficiency in production. Thus, in the model, the impact of digital transformation can be abstractly classified into two core domains: capital efficiency and labour efficiency.

Importantly, it must be recognized that the deployment of digital transformation also incurs additional costs for a firm (F. Li, 2020). Hence, the application of digital transformation has a multidimensional influence on a firm's capital efficiency, labour efficiency, and the extra costs of digital adaptation.

In the following model specifications, the impacts of digital transformation on these three dimensions will be formally articulated, thereby providing a robust theoretical foundation to understand its overall effects on firms. The overall analysing roadmap is described in Figure 2:

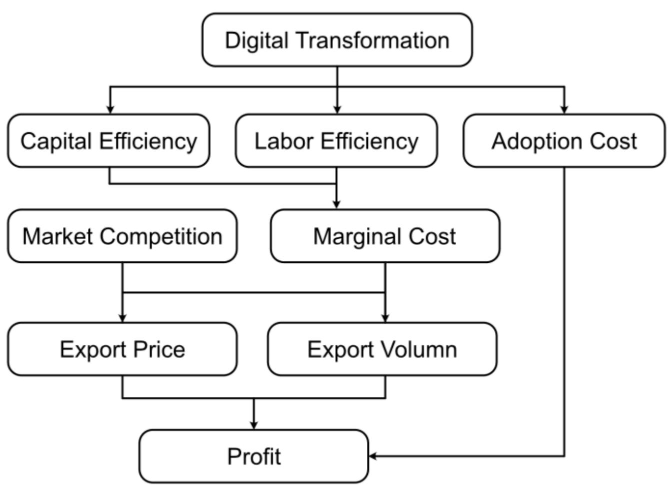


Figure 2. Analysing roadmap

2.2.2. The Utility of Consumers

The model employs the fundamental principles of general equilibrium theory and posits an economy comprising two main sectors: households and firms. In this configuration, households operate under a Constant Elasticity of Substitution (CES) utility function, inspired by the seminal works of export-related works (Krugman, 1979, 1980). In the model, households derive utility from a continuum of goods, denoted by X, with the utility function taking the form:

$$U = \left[\int_{x \in X} c(x)^{\frac{\varepsilon - 1}{\varepsilon}} d\, x \right]^{\frac{\varepsilon}{\varepsilon - 1}} \tag{1}$$

Here, ε represents the elasticity of substitution among goods in the market, higher ε implies higher market competition (Bajzik et al., 2020). Under this CES framework, when consumers reaches utility maximization condition, the equilibrium relationship between consumer demand and the price of the good x is expressed as (Dixit & Stiglitz, 1977):

$$c(x) = \frac{w}{P} \left(\frac{p(x)}{P} \right)^{-\varepsilon} \tag{2}$$

Where P represents the aggregate price index and w indicates the wage rate. Equation (2) establishes the relationship between product prices and demand quantities based on market demand conditions. Notably, the households' consumption decisions here feed back into the firm's revenue and pricing strategies. In this general equilibrium setting, the product prices $p(x)$ is endogenously decided alongside with the wage index w. This implies that when firms change their production scale or adopt digital transformation measures that affect labour demand, the equilibrium wage rate may adjust, which in turn affects households' income and consumption demand. Hence, the utility-maximization problem of households and the profit-maximization problem of firms are jointly solved to yield an equilibrium solution for both wages and product prices.

The price-demand function in Equation (2) indicates the product market clearing condition in the equilibrium model, representing the market's demand response to the pricing of the firm's products.

2.2.3. The Production

After considering the consumer utility maximization and product market clearing conditions, this subsection pays attention to the production process.

While Melitz's model framework specifies labour as the sole input factor in the production function, thereby significantly simplifying the complexity of solving the model, this assumption overlooks the multidimensional impact of digital transformation on firms (Melitz, 2003). Therefore, it is essential to consider multiple input factors within the model and to identify the differential effects of digital transformation on these inputs.

To address this limitation, this paper incorporates a Constant Elasticity of Substitution (CES) production function. The flexibility of the CES production function allows firms to produce goods using a combination of various inputs, thereby capturing the heterogeneous impacts of digital transformation across different factors. Formally, a firm's production function is specified as follows:

$$y = \left[\sum_{i=1}^{N} \theta_i (\alpha_i x_i)^{\rho}\right]^{\frac{\gamma}{\rho}} \tag{3}$$

In Equation 3, y represents the firm's output, x_i denotes the quantity of each input factor employed, and α_i corresponds to the efficiency associated with each input factor. The parameter θ_i indicates the share parameter of input factor i. The production function is assumed to exhibit constant returns to scale and unit elasticity of substitution between capital and labour ($\gamma = 1$). For simplicity, the elasticity of substitution between capital and labour is introduced as $\sigma \equiv 1/(1 - \rho)$ (Arrow et al., 1961).

To comprehensively capture the impact of digital transformation on firms' capital and labour efficiency, this section adopts a unified framework for analysis. In general, the relationship between a firm's digital transformation and efficiency is specified as a general form:

$$\alpha_i(\delta) = \beta_i \cdot \delta^{r_i} + \phi_i \tag{4}$$

In this context, i denotes different input factors. Here we rewrite α_i as $\alpha_i(\delta)$, represents the efficiency of input factor i as a function of the level of digital transformation δ. β_i indicates the marginal impact of digital transformation on the efficiency of input factor i, and ϕ_i denotes the efficiency of input factor i before adopting digital transformation. The parameter r_i reflects the returns to scale characteristics of the efficiency improvement due to digital transformation for each input factor. By adjusting the value of r_i, we can represent different returns to scale scenarios.

When $r_i > 1$, it signifies that the impact of digital transformation on input factor efficiency exhibits increasing returns to scale, implying that the marginal benefits of digital investment are rising. Conversely, when $r_i = 1$, the effect of digital transformation on efficiency follows constant returns to scale. Here, efficiency becomes a linear function of digital transformation, each additional unit of digital investment leads to a fixed proportional increase in efficiency. This scenario applies when digital technologies are mature, and their benefits are predictable, indicating that the impact of digital transformation on efficiency grows proportionally. Finally, when $r_i < 1$, it indicates that the impact of digital transformation on input factor efficiency exhibits decreasing returns to scale, reflecting diminishing marginal returns possibly due to technological limitations or increased complexity.

In practical business operations, converting various resource inputs into output products or services involves a complex process. These inputs are not narrowly confined to raw materials but encompass a broader spectrum of resources, such as human capital and equipment investments. As previously mentioned, digital transformation differs from traditional technological progress in that it affects various types of inputs within a firm's production process, and these effects may not be uniform across all inputs. Consequently, each input factor i in the firm is associated with specific parameters β_i, r_i, and ϕ_i.

However, the primary focus of this paper is not to detail the specific scope and all possible types of inputs but to establish a general framework wherein digital transformation heterogeneously influences multiple production factors within firms. To facilitate analysis and ensure the tractability of the model, we uniformly set r_i to 1 in our model specification. Moreover, we concentrate on the two most representative input factors in the production process: capital and labour.

Hence, digital transformation exerts tangible impacts on capital efficiency and labour efficiency. Note the number of input factors are not necessarily limited to two aspects, Equation 4 is rather flexible and could be extended to more factors if necessary. As discussed earlier, these impacts are not necessarily homogeneous across all components of production. In this model, a firm's degree of digital transformation δ enhances capital efficiency $\alpha_1(\delta)$ like advanced equipment and increases labour efficiency $\alpha_2(\delta)$ such as the usage of more effective and advanced management systems.

Formally, the relations are expressed as $\alpha_1(\delta) = \phi_1 + \beta_1\delta$ and $\alpha_2(\delta) = \phi_2 + \beta_2\delta$. Here, ϕ_1 and ϕ_2 represent the baseline efficiencies for capital and labour before adopting digital transformation. β_1 and β_2 quantify the marginal change in capital and labour efficiencies for each unit increase in the degree of digital transformation δ. Consequently, $\alpha_1(\delta)$ and $\alpha_2(\delta)$ are both linear functions of δ, enabling a dynamic analysis of how varying levels of digital transformation affect production efficiencies.

Thus, in the model, the production function considering digital transformation turns into:

$$y = [\theta[(\phi_1 + \beta_1\delta)k]^\rho + (1-\theta)[(\phi_2 + \beta_2\delta)l]^\rho]^{1/\rho} \tag{5}$$

Through these specifications, the model lays the foundation that digital transformation affects the firm's production process by affecting the production efficiency of input factors separately.

2.2.4. The Costs

In the production and business activities of firms, there are primarily direct cost and indirect cost involved (Das et al., 2007; Xu et al., 2024). The examination begins with the direct cost, referring to marginal cost of producing each unit of good y in the model. The subsequent discussion pertains to the indirect cost.

The marginal cost (MC) is influenced by the amounts of capital (k) and labour (l) used, along with the price of capital (p_k) and labour wages (w). The capital and labour required per unit output y are $\frac{\partial k}{\partial y}$ and $\frac{\partial l}{\partial y}$ respectively. Hence, the expenses on capital and labour are $p_k \cdot \partial k/\partial y$ and $w \cdot \partial l/\partial y$. Subsequently, incorporating equation (4) into the analysis, the marginal cost (MC) for producing one unit of product y is derived as follows:

$$\begin{aligned} MC \quad &= \frac{\partial k}{\partial y} \cdot p_k + \frac{\partial l}{\partial y} \cdot w \\ &= \lambda \left[\frac{p_k}{\pi} \cdot k^{1-\rho} \cdot (\phi_1 + \beta_1\delta)^{-\rho} + \frac{w}{1-\pi} l^{1-\rho} \cdot (\phi_{02} + \beta_2\delta)^{-\rho}\right] \end{aligned} \tag{6}$$

in which:

$$\lambda = [\theta[k \cdot (\phi_1 + \beta_1\delta)]^\rho + (1-\theta)[l(\phi_2 + \beta_2\delta)]^\rho]^{\frac{\rho-1}{\rho}} \equiv f_\lambda(k, l, \delta) \tag{7}$$

It is evident here that the marginal cost of a firm depends on three endogenous variables: the amount of capital input (k), the quantity of labour input (l), and the degree of the firm's digital transformation (δ). For ease of readability and further formula derivation in this context, the value of equation (6) is denoted as $f_\lambda(k, l, \delta)$, indicating its dependence on the three endogenous variables: k, l, and δ.

The indirect cost originates from three main sources: Firstly, the fixed cost c_f, necessary for maintaining operations of the firm, which are not directly linked to the firm's produce or export activities or level of digital transformation (Saravia & Voigtländer, 2012). Secondly, the additional costs associated with exporting products c_e, commonly referred to as iceberg costs (Combes et al., 2012; Melitz, 2003), which refers to a ratio related to the overall production volume y. Lastly, the cost of implementing digital transformation c_d, which is unrelated to the output quantity y but directly connected to the degree of digital transformation firm applied (δ) (Gebauer et al., 2020). In detail, the indirect cost ($IndCost$) of a firm includes:

$$IndCost = c_f + c_e \cdot y + c_d \cdot \delta \tag{8}$$

Overall, both direct and indirect costs of firms are considered in the model. The marginal and iceberg costs are closely related to the production volume, while the cost of digital transformation depends on the depth of its application. Finally, the fixed cost only depends on whether a firm stays alive in the market or not.

2.3. The Equilibrium

After discussing market demand, the production process, and the costs of firms, a set of conditions is now required to determine the equilibrium state of the firms and consumers. The achievement of general equilibrium conditions requires two categories comprising four conditions.

The first category pertains to the optimization strategies of economic participants, specifically the utility-maximization strategy of consumers, and the profit-maximization strategy of firms, which involves considerations of efficiency improvements and additional costs arising from digital transformation.

The second category relates to market-clearing conditions in both factor and final goods markets. For factor markets, equilibrium requires maintaining appropriate proportions of labour and capital inputs, resulting in balanced wage levels. For the final product market, equilibrium conditions involve determining the final sales price and volume of products through the price-demand mechanism. When these four conditions are simultaneously satisfied, the economy reaches a state of general equilibrium.

2.3.1. Optimization strategies of firms and individuals

For the consumers, their equilibrium strategies are determined by the utility function, the wage rate, as well as the price of the output goods. The market competition factor which may affect the price-demand relationship is also considered. As mentioned in Equation (2), the price-demand relationship under equilibrium is illustrated below:

$$c(x) = \frac{w}{P}\left(\frac{p(x)}{P}\right)^{-\varepsilon}$$

For the firms, they are required to meet the profit maximization condition, ensuring rational allocation of production resources. In this context, "optimized input allocation" refers to the allocation between capital (k) and labour (l). In the production function, the optimal distribution of production inputs is achieved when the marginal output per unit of capital investment equals the marginal output per unit of labour investment. This means, under profit maximization condition, the additional output (y) generated by spending one unit of cost on capital and labour is identical. In the specification, $\partial y/\partial k$ represents the output produced by investing one unit in capital k. This value is then divided by the price of capital p_1, resulting in $\frac{\partial y/\partial \mathrm{k}}{p_k}$ units of output per unit of money invested in capital. Similarly, the output generated by spending one unit of money on labour l is$\frac{\partial y/\partial l}{w}$. Under profit maximization condition, the following equation is obtained:

$$\frac{\partial y/\partial k}{p_k} = \frac{\partial y/\partial l}{w} \tag{9}$$

By solving Equation (9), the optimal resource allocation condition can be obtained in the form of a relative relationship between k and l.

$$\frac{k}{l} = \left[\frac{p_k}{w} \cdot \frac{1-\theta}{\theta} \cdot \left(\frac{\phi_2 + \beta_2\delta}{\phi_1 + \beta_1\delta}\right)^{\rho}\right]^{\frac{1}{\rho-1}} \equiv f_k(\delta) \tag{10}$$

In equation (10), it is evident that the only endogenous variable influencing the optimal input ratio of capital and labour is the degree of a firm's digital transformation (δ). Additionally, exogenous variables such as the relative prices of capital and labour (p_1/w), the share parameter of capital in production (θ), initial values of digital capital efficiency (ϕ_1) and labour efficiency (ϕ_2), and the impact of digital transformation on these efficiencies (β_1 and β_2) all affect the optimal allocation of resources. For convenience in subsequent equations and equilibrium solutions, the result of k/l is represented as $f_k(\delta)$, indicating that this expression represents the value of k relative to l, and contains only δ as an endogenous variable.

After determining the optimal allocation ratio of labour and capital inputs, by substituting equation (10) into equation (6), the marginal cost of production for a firm is derived under the principle of cost minimization:

$$MC = f_\lambda(\delta)\left[\frac{p_1}{\theta} f_k(\delta)^{1-\rho}\alpha^{-\rho} + \frac{w}{1-\theta}\beta^{-\rho}\right] \tag{11}$$

In which:

$$\begin{aligned}
f_\lambda(\delta) &= [\theta f_k(\delta)^{\rho}\alpha^{\rho} + (1-\theta)\beta^{\rho}]^{\frac{\rho-1}{\rho}} \\
f_k(\delta) &= \left[\frac{p_k}{w}\frac{1-\theta}{\theta}\left(\frac{\beta}{\alpha}\right)^{\rho}\right]^{\frac{1}{\rho-1}} \\
\alpha &= \phi_1 + \beta_1\delta \\
\beta &= \phi_2 + \beta_2\delta
\end{aligned}$$

Under the condition of cost minimization for firms, the variable l is eliminated, leaving the degree of digital transformation δ as the sole endogenous variable affecting the marginal cost of the firm's product. Consequently, $f_\lambda(k, l, \delta)$ is revised to $f_\lambda(\delta)$.

Then, combining the derivation of marginal cost of production and the cost function, the total production cost and profit function Π are derived as below, the firms will maximize the profit function in their strategy:

$$\Pi = \underbrace{y \cdot p(y)}_{Payoff} - \underbrace{(k \cdot p_k + l \cdot w)}_{Direct\ Cost} - \underbrace{(c_f + c_e \cdot y + c_d \cdot \delta)}_{Indirect\ Cost} \tag{12}$$

2.3.2. Clearing conditions in both goods and labour markets.

In terms of final goods market clearing condition, the demand for a product $c(y)$ equals its supply y, allowing us to establish:

$$y = c(y) \tag{13}$$

Drawing on Krugman's (1979) discussion, in a monopolistically competitive market where products clear the market, the price of the product meets to the following equation:

$$p(y) = \frac{\varepsilon}{\varepsilon - 1} \cdot MC \tag{14}$$

Equation (14) indicates that the final selling price of a product depends on two key factors: the marginal cost (MC) of producing the product and the intensity of market competition, denoted by ε. A higher value of ε signifies fiercer competition, leading to a lower margin of profit ratio $\varepsilon/(\varepsilon - 1)$ and a lower markup on each product sold, bringing the selling price closer to the marginal cost of production.

By incorporating equations (2) and (12) into equation (11), the firm's equilibrium output y under final good market clearing can be solved as:

$$y = w \cdot P^{\varepsilon - 1} \cdot \left(\frac{\varepsilon}{\varepsilon - 1} \cdot MC\right)^{-\varepsilon} \tag{15}$$

Regarding the labour market clearing, by substituting equations (10) and (13) into equation (4), the labour input l under equilibrium output is determined:

$$l = \frac{w \cdot P^{\varepsilon - 1}\left(\frac{\varepsilon}{\varepsilon - 1} MC\right)^{-\varepsilon}}{[\theta \alpha^{\rho} f_k(\delta)^{\rho} + (1 - \theta)\beta^{\rho}]^{1/\rho}} \tag{16}$$

In which:

$$\begin{aligned}
MC &= f_\lambda(\delta)\left[\frac{p_k}{\theta} f_k(\delta)^{1-\rho}\alpha^{-\rho} + \frac{w}{1-\theta}\beta^{-\rho}\right] \\
f_\lambda(\delta) &= [\theta f_k(\delta)^{\rho}\alpha^{\rho} + (1-\theta)\beta^{\rho}]^{\frac{\rho-1}{\rho}} \\
f_k(\delta) &= \left[\frac{p_k}{w}\frac{1-\theta}{\theta}\left(\frac{\beta}{\alpha}\right)^{\rho}\right]^{\frac{1}{\rho-1}} \\
\alpha &= \phi_1 + \beta_1\delta \\
\beta &= \phi_2 + \beta_2\delta
\end{aligned}$$

Then the capital input k under equilibrium is determined as well:

$$k = l \cdot f_k(\delta) \tag{17}$$

In which:

$$\begin{aligned} f_k(\delta) &= \left[\frac{p_k}{w}\frac{1-\theta}{\theta}\left(\frac{\beta}{\alpha}\right)^{\rho}\right]^{\frac{1}{\rho-1}} \\ \alpha &= \phi_1 + \beta_1\delta \\ \beta &= \phi_2 + \beta_2\delta \end{aligned}$$

Having determined the equilibrium quantities for a firm's labour input (l), capital input (k), direct production cost (MC), and indirect cost ($IndCost$), as well as the equilibrium output (y) and price $p(y)$, the model is now in a position to match the state of equilibrium. By substituting equations (5), (8), (11), (15), (16), and (17) into equation (12), the profit of a firm in its equilibrium state can be derived. Since this solution involves only one endogenous variable, the degree of the firm's digital transformation δ, we denote it as $f_{\Pi}(\delta)$, meaning $f_{\Pi}(\delta) \equiv \Pi$.

To summarize, the general equilibrium model requires the following conditions clear simultaneously. Firstly, the 2.3.1 section ensures that both firms and individuals are under optimal strategies. Secondly, the 2.3.2 section clarifies that both goods and labour markets are cleared simultaneously. Under these conditions, the general equilibrium condition is achieved.

2.3.3. Further discussion on the model

In the traditional Melitz model, firms' efficiencies across the market are assumed to follow a Pareto distribution, with the equilibrium production efficiency serving as the threshold for firms' entry and exit. In our model, however, the entry and exit thresholds are defined as functions closely linked to digital transformation.

Specifically, within the framework of our model, the degree of a firm's digital transformation (δ) is directly linked to its capital and labour efficiencies. Once a firm's level of digital transformation larger than the entry threshold (where $f_{\Pi}(\delta) = 0$), it attains sufficient production efficiency and cost-control capability to enter export markets ($\Pi > 0$). Conversely, firms already operating in export markets may exit if their level of digital transformation and associated efficiencies fall below this threshold.

Moreover, firms in the export market with higher degrees of digital transformation (δ) can further enhance their capital and labour efficiencies, thus reducing marginal production costs (MC). Consequently, under equilibrium conditions, these firms can offer products at lower selling prices $p(y)$, achieve higher sales volumes (y), and ultimately generate greater profits ($f_{\Pi}(\delta)$). Nevertheless, the costs associated with digital transformation must not be overlooked. Higher levels of digital transformation entail greater indirect costs ($IndCost$), which may have negative impact on profits in export market.

In terms of time scope, the short run and long run effects of digital transformation on the market are diverse. Specifically, in the short run, the parameters affecting firms' entry thresholds such as the elasticity of substitution among products (ε) and the price index of the goods (P) remain unchanged, as firms' digital transformation does not immediately affect these market-level parameters. Thus, firms that successfully achieve efficiency gains and cost reductions from digital transformation can realize higher short-term profits ($f_{\Pi}(\delta)$). However, in the long run, as firms continually enter and exit markets, market competition get stronger, leading to changes in the market-level parameters. Eventually, under conditions of long-term equilibrium, firms experience declining equilibrium profits, ultimately converging toward zero profits and forming a perfectly competitive market structure.

Apart from the degree of digital transformation δ, factors such as the baseline production efficiency of firms' input factors (ϕ_i) and the marginal impact of digital transformation (β_i) also influence firms' entry and exit decisions. However, these factors are part of the firms' endowments, which they cannot modify to improve their circumstances. The only variable that firms can actively control is the degree of digital transformation. Therefore, in the subsequent data calibration, we focus primarily on this endogenous variable—the degree of digital transformation.

2.4. Taking the Model to the Data

After discussing how market competition and digital transformation affect the two efficiencies and then the impact on firm's export and profits under equilibrium, the real-world data is still required to calibrate the model and give support to the discussion. Therefore, our attention shifts to understanding the concrete outcomes of such influences in a real economy. Firstly, a calibration is concluded to ensure that the parameters in the model closely resemble real-world scenarios. Secondly, through simulation, exploration will be made into how a firm's resource allocation, costs, and profits vary with the degree of digital transformation under different levels of market competition and heterogeneous effects of digital transformation.

2.4.1. Data Source

This model is constructed on a general framework and becomes applicable for simulating local firms' exports once calibrated with region-specific data. Given the vast number of countries and the significant differences in their geographical environments and economic structures, the estimated parameter values can vary considerably depending on the country selected. Therefore, in this study, Chinese firms are chosen as the primary data source, supplemented with international data from various other countries.

For the reasons of using Chinese firms data, firstly, the study primarily explores the impact of digital transformation on firms' export behaviours and performance, with Chinese firms at the forefront of the digital economy's rapid development (W. Li & Li, 2022; F. Wang et al., 2023; F. Wang & Ye, 2023). Therefore, the scale of digital transformation among Chinese firms has already reached a significant level and has entered a mature phase, aligning closely with our research objectives compared to many other economies where digital transformation is either in its infancy or early stages (Vial, 2019). Secondly, China has become one of the world's largest exporting economies (Yue, 2023), plays a pivotal role in the global economy through its firms' export activities (Deng et al., 2022). Utilizing Chinese exporting firms as a calibration benchmark offers sufficient representativeness. Therefore, considering both the development level of digital transformation and the scale of exports, employing Chinese firms as the data baseline for calibration presents irreplaceable advantages.

In this model, integrating international data is also essential. For a general equilibrium models, the calibration process typically involves extracting key supply-side parameters from corporate data and key demand-side parameters from household surveys, supplemented by certain macroeconomic parameters (Iskrev, 2019). Unlike traditional general equilibrium models, the model incorporates firms' export behaviours, indicating that firms' economic activities are related to multiple countries (Caliendo et al., 2019). Firms initially invest in input factors and spend costs to produce goods in the exporting country; subsequently, they engage in market competition in the importing country to pin down the prices and then sell products. During the calibration process, it is essential to consider parameters related to production in the exporting country and those related to sales in the importing country. Relying solely on data from a single country is far from sufficient. To facilitate parameter calibration, market and macroeconomic data from major world economies have been integrated.

In the following subsections, the data sources and calibration process for each parameter will be delineated individually.

2.4.2. Exogenous Parameters

The parameters required to be calibrated are divided into four groups, related to household preference, market factors, production process and digital transformation, respectively.

The wage and price index

In the model, the absolute value of employee wage levels is not of primary interest. Instead, the focus is more on the relative values of capital costs and market price indices based on wages (Combes et al., 2012). Therefore, following the convention in the existing literature, the wage level of employees is standardised to 1 (Dinlersoz & Wolf, 2023; Feliciano-Cestero et al., 2023; Melitz, 2003; Zhu, Zeng, et al., 2021). This approach helps eliminate the effects of inflation and simplifies the model for clearer analysis. Based on the standardised wage level, the prices can be calibrated with localized data sources.

In terms of the wage, we rely on the China Household Finance Survey (CHFS) to obtain an estimate of the average wage rate for three main reasons. Firstly, while firm-level wage data exist in certain proprietary or fragmented databases, the CHFS stands out for its broad coverage and representativeness of the Chinese population's labour income. Secondly, for our general equilibrium model, which focuses on aggregate wage levels rather than firm-specific wage dispersion, this representative average wage is both sufficient and appropriate (T. Tang et al., 2023). Thirdly, this approach aligns with previous macroeconomic modelling studies (Combes et al., 2012; Dinlersoz & Wolf, 2023) that employ household surveys to calibrate a baseline wage or labour income, especially when detailed firm-level wage data are either unavailable or less reflective of the overall economy.

In this survey questionnaire, this part analysed the primary consumption expenditures of households through questions G1001 to G1029 in the 'Expenditure and Income' section. Then absolute price level of a basket of goods was calculated by considering these expenditures and dividing by the average number of adults per household, as suggested in the literature. Then, by dividing this figure by the average annual income per household member, the relative relationship between the market price index and wages were determined, represented as P/w. Since the model section have normalised wages to 1, P/w equals P. Based on the estimates, the average ratio of the price of consumer products to wage levels is approximately 0.251. Thus, in the calibrated model, the price index was set to $P = 0.251$.

Elasticity of substitution among goods

For this model, it is essential to consider the degree of competition faced by firms when selling their products in markets. To estimate this parameter, here followed the approach of the existing literature, reviewing 84 estimates of the elasticity of substitution among consumption goods from 64 publications since 1995 (Bajzik et al., 2020; Costinot & Rodríguez-Clare, 2018; Fontagné et al., 2019). These data encompass estimates for all major economies in North America, Europe, and Asia. Our analysis of these statistics reveals that the elasticity of substitution among consumption goods ε primarily ranges between 0 and 8, with its distribution illustrated in Figure 3:

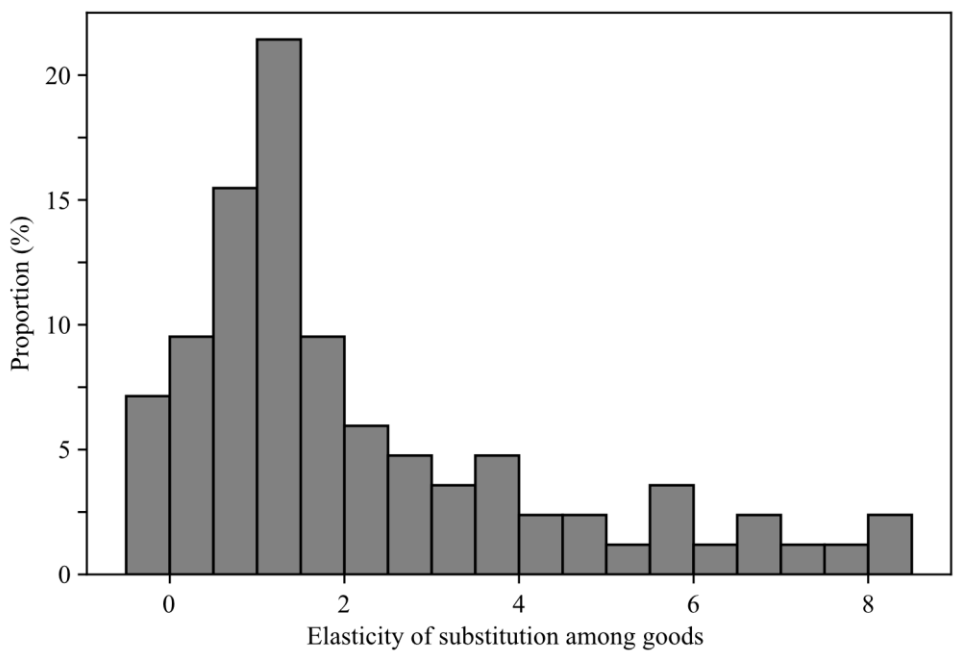


Figure 3. Distribution of elasticity of substitution among goods

Firstly, based on its statistical characteristics, the historical average of these estimates was used as the value of $\varepsilon = 2.202$ in this model. Considering the significant heterogeneity in competition that firms face while exporting products to different markets, this part further relaxed this parameter setting in our subsequent analysis. The elasticity of substitution (ε) was treated as a critical market characteristic parameter here, setting three representative market conditions: low competition ($\varepsilon = 2$), medium competition ($\varepsilon = 4$), and high competition ($\varepsilon = 6$). Then there will be a discussion on different market competitions, how a firm's product pricing, export volumes, and profits vary with the degree of digital transformation.

Elasticity of substitution between capital and labour

For estimating the elasticity of substitution between capital and labour for firms, the approach of Knoblach and Stöckl was adopted, extracting 105 different estimates of elasticity of substitution from 58 publications spanning from 1980 to 2020 (Knoblach & Stöckl, 2020). To ensure the accuracy of the parameter estimation, the selected literature encompasses studies on countries in the Americas, Europe, and Asia. Then all these estimates were statistically compiled and organized, calculating an average value to use as the parameter in the model (Klump et al., 2007). Consequently, the estimated value of elasticity of substitution in this model is $\sigma = 0.689$, with its descriptive statistics presented in Figure 4.

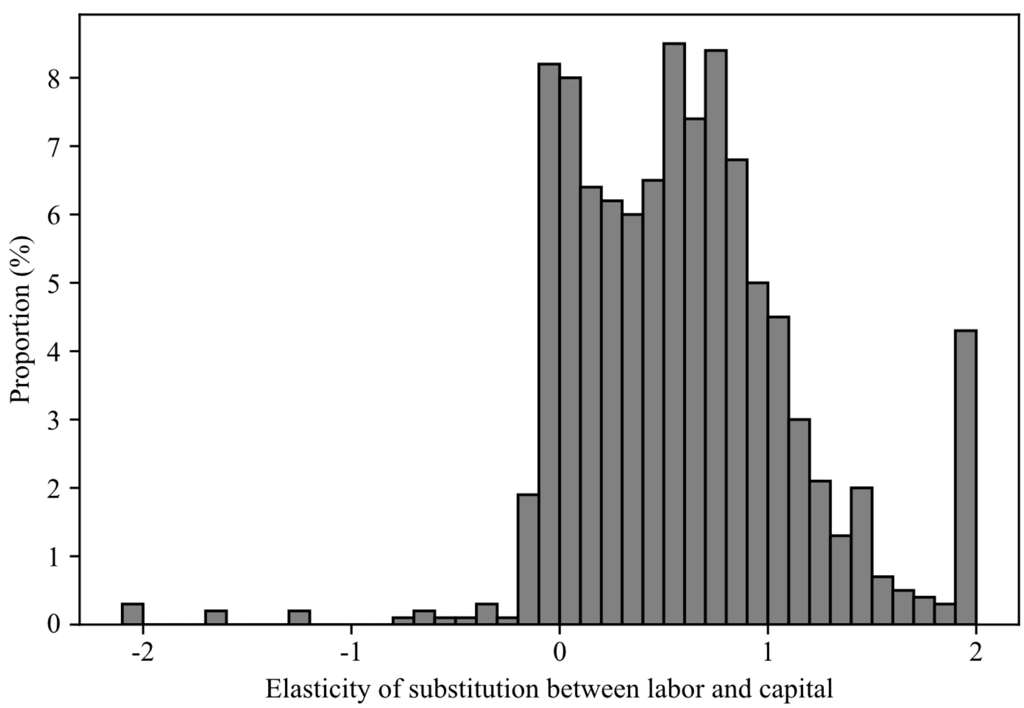


Figure 4. Distribution of elasticity of substitution between labour and capital

Capital share in production

Numerous papers have already conducted measurements and calibrations of the capital share. This approach has compared both traditional and recent literature (Fernández-Villaverde et al., 2016; Iskrev, 2019; Schmitt-Grohé & Uribe, 2012; Smets & Wouters, 2007; Walker, 1969). The model setup considers a monopolistically competitive market, exports, and certain macroeconomic perspectives. After comparing the applicability of various optional estimated values, this approach finally use the capital share calculated in Schmitt-Grohé and Uribe's medium-scale real business cycle model as our benchmark (Schmitt-Grohé & Uribe, 2012). In their estimation, the capital share is valued at $\theta = 0.225$.

2.4.3. Estimating Digital Transformation

In terms of the parameters related to the firm's digital transformation, a unique text-based analysis method to measure them was developed. Although there has been substantial discourse on the implications of digital transformation, a consensus on the measure of business digital transformation remains elusive. Currently, the measurement methods for digital transformation are mainly divided into three categories. (1) Methods based on city proxy indicators. These studies use the digital economy development indicators of the city where the company is located as a proxy variable for the degree of business digital development (Abeliansky & Hilbert, 2017). (2) Classification method. Containing binary classification method (Bharadwaj et al., 2013; F. Li et al., 2016) and Likert scale ranging method (Alsheibani et al., 2018; Denicolai et al., 2021). This method divides businesses into whether and the extend they have undergone industrial digital transformation and uses "0-1" dummy or "1-5" scale variables to depict this. (3) Methods based on unstructured data indicators. This method uses unstructured data such as text data and image data from the announcement and news to depict the degree of a firm's digital transformation (George et al., 2021; Ghasemaghaei et al., 2017; G. Kim et al., 2011).

While the first two categories of measurement for digital transformation possess the strength of convenient data acquisition and straightforward computation, they are overly coarse and simplistic. Such measures struggle to capture the fine-grained distinctions in the extent of digital transformation across individual enterprises.

To accurately measure the degree of digital transformation, this section follow the practice of Bodnaruk and Hoberg & Phillips to conduct a text-based digital transformation measurement method (Bodnaruk et al., 2015; Hoberg & Phillips, 2016). The methodology is shown in Figure 5.

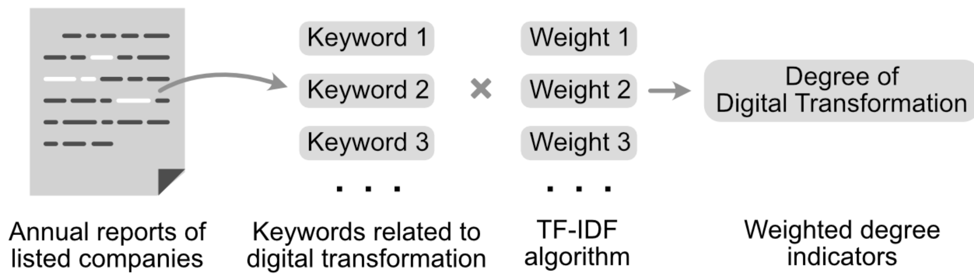


Figure 5. Methodology of estimating digital transformation

Firstly, a Python web scraping algorithm was applied to extract text data from the annual reports of all A-share listed companies from 2010 to 2020. The data fetched is processed into unstructured annual report text pools.

Secondly, the keywords related to the topic of digital transformation according to authoritative documents published by the Chinese government were determined, such as "China Digital Economy Development White Paper (2021)". After that a screening process was adopted to the above-mentioned text data pool to fetch the frequency of occurrence. In contrast to the existing literature that merely aggregates the frequency of terms associated with digital transformation, this approach employs a refined Term Frequency-Inverse Document Frequency (TF-IDF) algorithm, grounded in ontology relevance (Ramos, 2003). This nuanced algorithm serves dual purposes: it assigns greater weight to the terms frequently cited in the government documents concerning digital transformation, thereby enhancing their significance in the analysis. Concurrently, it penalizes the terms that are ubiquitously present across multiple documents to mitigate the risk of estimation bias.

Finally, considering the sustained impact of a firm's digital transformation on businesses across multiple years, this paper innovatively uses annual cumulative values to measure the degree of business digital transformation. Since this variable is essentially the weighted frequency of terms related to digital transformation mentioned in the annual report, this part also logarithmically processes this variable to maintain a balance that is both discriminating but not completely linear in unbounded growth. The descriptive statistics for the full sample and annual estimates of the degree of digital transformation are presented in Table 1.

It is observed that from 2010 to 2020, there was a steady upward trend in the degree of digital transformation among firms in China. Meanwhile, the variability among firms (as indicated by the standard deviation) was increasing. This suggests that although the overall level of digital transformation among Chinese enterprises has been rising annually, the divergence between them has also been widening. Not all firms have deeply advanced their digital transformation initiatives, and some have not implemented digital transformation at all.

Table 1. Summary descriptive statistics of δ by year

Year	N	Mean	SD	Min	Median	Max
2010	1899	0.121	0.272	0.000	0.027	2.897
2011	2149	0.146	0.309	0.000	0.035	2.753
2012	2270	0.164	0.329	0.000	0.046	2.935
2013	1772	0.193	0.363	0.000	0.057	2.738
2014	2401	0.232	0.403	0.000	0.072	3.150
2015	2592	0.310	0.478	0.000	0.121	3.596
2016	2829	0.383	0.544	0.000	0.174	3.848
2017	3317	0.469	0.605	0.000	0.232	4.044
2018	3389	0.562	0.677	0.000	0.302	4.382
2019	3503	0.652	0.714	0.000	0.398	4.501
2020	3531	0.813	0.804	0.000	0.566	4.954
Total	29652	0.415	0.609	0.000	0.155	4.954

Till now, the degree of digital transformation of firms have been successfully estimated, which is a core variable (δ) in the model. Subsequently, the capital and labour efficiencies of firms is further estimated. Capital efficiency in the model is conceptualized as the output-to-input ratio in terms of capital, reflecting the increase in output quantity y per unit of capital input k. Considering the wide variations in capital types, prices (p_1), types of outputs, and their prices $p(y)$ across different real-world firms, using direct measures of capital usage and output quantity could introduce significant errors in empirical estimations (Kurz & Salvadori, 2014; Meade, 2010; Miller & Blair, 2009; Raa & Rueda-Cantuche, 2005; Salvadori, 2014). Therefore, to ensure consistency in empirical estimations, the volume of capital input and output quantity were replaced with their market values (Raa, 2017). Under this setting, a firm's capital efficiency is represented as its return on capital investment, empirically estimated using the ratio of a firm's sales revenue to its total assets. Similarly, labour efficiency is defined as the return on labour investment, estimated in this study by the ratio of a firm's sales revenue to its wage expenditures. The data for estimations above was sourced from the balance sheets and income statements in the annual reports of Chinese listed companies, with supplementary data from the Chinese Research Data Services Platform (CNRDS database).

Following the empirical estimations, the impact parameters of Digital Transformation on Capital efficiency and Labour efficiency are $\phi_1 = 2.376$, $\beta_1 = 0.0314$, $\phi_2 = 1.535$, $\beta_2 = 0.0566$. Thus, the relevant parameters for equation (5) are as follows:

$$\alpha = \phi_1 + \beta_1\delta = 2.376 + 0.0314 \times \delta$$

$$\beta = \phi_2 + \beta_2\delta = 1.535 + 0.0566 \times \delta$$

The estimation results indicate that for firms without implying digital transformation, the average capital efficiency is approximately 1.6 times greater than labour efficiency. However, the impact of digital transformation on labour efficiency is about 1.8 times as much as capital efficiency. This finding suggests that, on average, a firm's initial capital efficiency is significantly greater than its labour efficiency. However, as firms implement digital transformation, this disparity diminishes and may theoretically reverse. These estimates demonstrate that, in general, digital transformation has a more pronounced positive effect on labour efficiency than capital efficiency. Details of the estimation and methodology for capital efficiency and labour efficiency are provided in Appendix B. Overall, the parameters calibrated are shown in Table 2:

Table 2. Results of parameter calibration

Parameter	Name	Mean	SD
	Household and Market		
w	Wage (Benchmark of prices)	1.000	0.000
P	Price index	0.251	0.151
ε	Elasticity of substitution among goods	2.202	2.669
	Production Process		
σ	Elasticity of substitution between k and l	0.689	0.303
θ	Capital share in production	0.225	-
	Digital Transformation		
δ	Degree of digital transformation	0.415	0.609
β_1	Impact of δ on capital efficiency	0.0314	0.011
β_2	Impact of δ on labour efficiency	0.0566	0.025
ϕ_1	Initial level of capital efficiency	2.376	1.089
ϕ_2	Initial level of labour efficiency	1.535	1.393

2.4.4. Simulation

Sections 4.1 and 4.2 have successfully estimated the core parameters of the equilibrium model. Recalling the motivation and significance of this study, the objective was to construct a general equilibrium model for enterprise exports that incorporates digital transformation. This model specifically considers the heterogeneous impact of digital transformation on firms' capital and labour efficiencies. Therefore, its primary goal is to provide enterprises with an optimal pathway for resource allocation under digital transformation. Furthermore, the model's equilibrium state involves analysing how digital transformation affects a firm's production, pricing, and profitability. It also offers insights into the optimal decisions for digital transformation in varying market environments.

The simulation process begins with discussing the optimal resource allocation and input ratios for firms. To understand the optimal input allocation, it is crucial to clarify the mathematical properties of equation (9). Equation (9) can be interpreted as a composite function, constituted by the marginal substitution elasticity (δ) and the relative efficiency of production inputs. Here

$f_e(\delta) = \frac{\phi_1+\beta_1\delta}{\phi_2+\beta_2\delta}$ represents the relative production efficiency of capital to labour. Therefore, equation (9) can be expressed as:

$$\begin{aligned}\frac{k}{l} &= \left[\frac{p_c}{w}\cdot\frac{1-\theta}{\theta}\cdot\left(\frac{\phi_2+\beta_2\delta}{\phi_1+\beta_1\delta}\right)^{\rho}\right]^{\frac{1}{\rho-1}} \\ &= \left(\frac{p_c(1-\theta)}{w\theta}\right)^{\frac{1}{\rho-1}}\cdot\left(\frac{\alpha}{\beta}\right)^{\frac{\rho}{\rho-1}}\end{aligned} \tag{18}$$

Equation (17) shows that the optimal production resource ratio for a firm consists of two parts. The first part is dependent on the input prices, participation ratios, and marginal rate of substitution in the production function, and is always greater than 0. The second part is influenced by the relative production efficiency of the inputs and the marginal rate of substitution elasticity. In the CES production function, where ρ falls within the range $\rho \in (-\infty, 1)$, the ratio k/l is positively correlated with relative production efficiency when $\rho < 0$, and negatively correlated when $\rho > 0$.

Regarding the ratio between capital efficiency and labour efficiency α/β, a formal expression goes like:

$$\frac{\alpha}{\beta} = \frac{\phi_1+\beta_1\delta}{\phi_2+\beta_2\delta}$$

In the absence of digital transformation, α/β depends on the initial production efficiency ϕ_1/ϕ_2. As the degree of digital transformation gradually increases, α/β progressively approaches the respective growth rates β_1/β_2 associated with digital transformation. Thus, the value of α/β should be within the boundaries between ϕ_1/ϕ_2 and β_1/β_2.

According to the parameters estimated, $\rho = -0.4514 < 0$, which suggests that in our parameter framework, a complementary relationship between labour and capital predominates. Furthermore, given that $\phi_1 > \phi_2$ and $\beta_1 < \beta_2$, the ratio α/β starts at the upper bound ϕ_1/ϕ_2, which exceeds 1 but decreases as firms progress in digital transformation, leading to a rise in the ratio of capital to labour. This outcome implies that in the production environment set by the model, digital transformation enhances labour efficiency more than capital efficiency. Due to the complementary relationship between capital and labour, firms should increase the proportion of input allocated to capital to ensure optimal production efficiency. Further, as the degree of digital transformation in firms increases, the optimal ratio of capital to labour input evolves as illustrated in Figure 6:

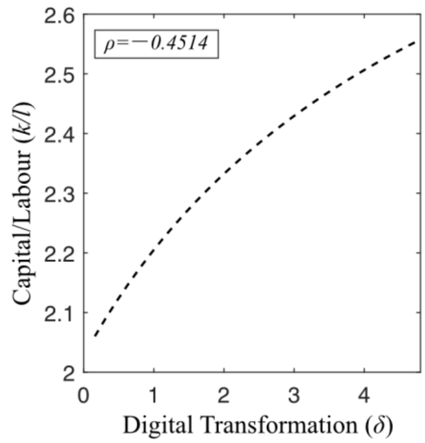


Figure 6. Optimal ratio of capital to labour

2.4.5. The Export Quantity and Profit Margin

In the setup of the model, firms face a variety of market environments when exporting goods, making the discussion of the optimal degree of digital transformation in different market contexts one of the key considerations of this paper. Based on the estimates in section 4.1, the elasticity of substitution in consumer preferences in overseas markets (ε) primarily ranges from 0 to 8. The changes in key indicators for firms exporting products to markets with different levels of competition, and how these indicators evolve with the degree of digital transformation. The results are shown in Figure 7. It is important to note that in our model, the firms with positive profit indicates they are able to enter the export market,

In different market competition environments, a firm's equilibrium product price, sales volume, and profits vary with digital transformation (Campa & Guillén, 1999). As this paper analysed in the process of solving the equilibrium, digital transformation enhances production efficiency, thereby reducing marginal production costs.

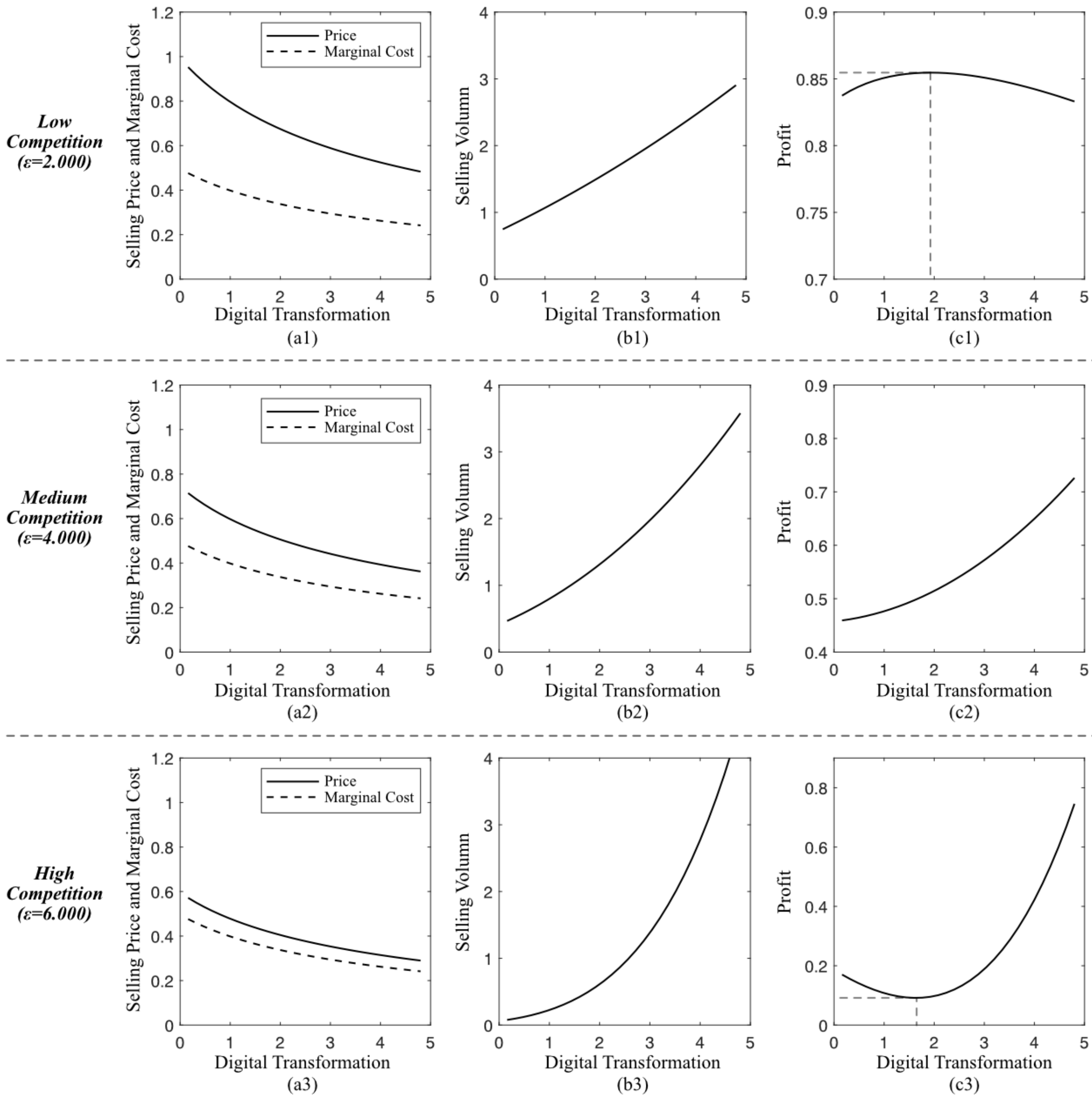


Figure 7. Prices, costs, selling volumes and profits under different market competitions

Low competition

In a low-competition environment, this transformation leads to lower marginal costs, enhancing market competitiveness and, correspondingly, increasing sales volumes (Hui, 2020). However, the decrease in costs and increase in sales do not monotonically increase profits due to two main reasons.

Firstly, in low competition markets, firms that have not yet implemented digital transformation often already have high marginal profits. While digital transformation reduces marginal costs of production, it also leads to significant marginal profit reductions. As depicted in

Figure 7. (c1), in monopolistically competitive markets, the price reduction often exceeds the decline in marginal costs, leading to a decrease in per-unit marginal profits. This effect is somewhat offset by increased sales volumes, as shown in Figure 7. (c1). Generally, excluding the additional costs of digital transformation, a firm's net payoff increases monotonically, though the rate of increase gradually diminishes.

Secondly, although a price drop can boost sales, the additional costs of digital transformation also rise with increasing sales volumes. The incremental costs of digital transformation turn high if firms intend to reach at higher sales volumes. Therefore, when a firm over-digitizes, its profits may not increase monotonically despite higher efficiency. For firms, higher levels of digital transformation mean higher costs, and lower marginal profits, though higher selling volume. Over digital transformation may even lead to a situation where additional profits cannot cover extra expenses, ultimately resulting in a decrease in profits (In Figure 7. (c1)).

In summary, in low-competition markets, during the initial stages of digital transformation, the marginal return exceeds the marginal cost of digital transformation. However, as the marginal return on efficiency gains diminishes, beyond a certain threshold, the marginal return on digital transformation falls below its marginal cost, leading to reduced profits. This results in an inverted U-shaped curve, as shown in Figure 7. (c1).

Medium Competition

In a medium competitive market, firms already operate at relatively lower marginal profits. Although digital transformation enhances efficiency and can reduce a firm's marginal profit, the increase in sales volume is more significant, serving as the dominant source of sales growth. In this scenario, the decrease in marginal profit due to digital transformation is smaller than the increase in sales volume. For firms, a higher level of digital transformation leads to higher payoffs. Moreover, the costs of further digital transformation are relatively stable compared to a low-competition market, resulting in a situation where the benefits of digital transformation always outweigh its costs. Consequently, increasing the level of digital transformation consistently enhances firm profits.

High Competition

In a highly competitive market, the marginal profits per product for firms are very low. The initial efficiency gains from digital transformation contribute minimally to sales, struggling to cover the costs of digital transformation. If a firm implements digital transformation but does not do so thoroughly, it could even result in profits falling below zero, potentially leading to market exit.

However, when the degree of digital transformation is sufficiently high, the decline in product profit becomes negligible, and the increase in sales volume starts to dominate. The impact of digital transformation on sales volume becomes more pronounced, significantly raising the per-unit benefits of digital transformation, eventually leading to higher profits in an equilibrium state.

It is noteworthy that even in moderate and high competition markets, where digital transformation can greatly enhance firm profits, they are still generally lower than in low-competition markets.

The results indicate that in low-competition markets, the dominant factor is the reduction in marginal profits brought about by digital transformation, which negatively impacts overall profits. Conversely, in high-competition markets, the increase in product sales volume due to digital transformation positively influences profits and becomes the prevailing factor.

Further, in markets with a high degree of monopoly, firms already secure sufficient profits through high marginal profits. Here, the payoff from digital transformation is consistently lower than its costs, leading to a negative impact on firm profits.

In summary, from a profitability perspective, digital transformation is not always beneficial for firms. When exporting to low-competition markets, moderate digital transformation can enhance profits, but excessive digitalization may reduce profits due to higher marginal costs and lower payoffs. Therefore, a moderate degree of digital transformation is the optimal strategy for firms exporting to low-competition markets (Figure 7. (c1)). In medium-competition markets, the payoff from digital transformation significantly outweighs its marginal costs, leading to higher profits. Thus, a deep and extensive implementation of digital transformation is the optimal strategy for firms exporting to these markets (Figure 7. (c2)). In high-competition markets, initial investments in digital transformation may decrease profits. However, when the degree of digital transformation is sufficiently thorough, the increase in sales volume becomes decisive, thereby improving profits. Consequently, for firms exporting to high-competition markets, the optimal strategy varies. More specifically, avoiding digital transformation is optimal when focusing on cost-saving, whereas extensive digital transformation is globally optimal when aiming to increase sales volume (Figure 7. (c3)).

2.4.6. Exit Risk and Availability of Firms

It is important to note that in markets with extremely high competition, the additional costs associated with digital transformation may lead to negative profits for firms. Our data and related literature suggest that the degree of digital transformation in enterprises is largely achieved incrementally rather than instantaneously (Micco, 2019; F. Wang et al., 2023; Wessel et al., 2021). This means that during the process of implementing digital transformation, firms may traverse the entire spectrum from low to high degree of digital transformation. For firms in highly competitive markets, there may be a stage called 'Death Valley' in the digital transformation process that results in negative profits. In this model, when firms export to a highly competitive market ($\varepsilon = 8$), firms may face negative profit when the digital transformation is started but not well applied. As is shown in Figure 8.

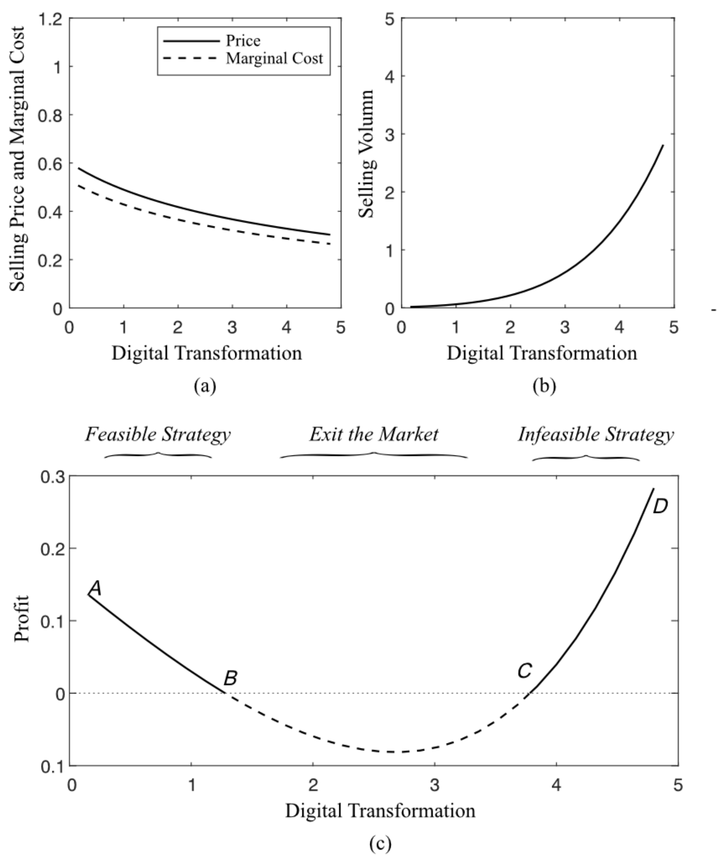


Figure 8. Firms under extreme market competitions

From subfigures (a) and (b) in Figure 8, when the degree of digital transformation is not high, the profit margin is low and the increase in selling volume is not high, resulting in profit cut. In this area, the local optimal strategy is applying no digital transformation at all (point A in subfigure (c)). When the positive effect of mass selling volume dominates with more thorough adoption of digital transformation, the profit ascends, and finally reaches the global optimal solution (point D in subfigure (c)).

According to Melitz's theory, negative profits in subgraph (c) imply that a firm's production efficiency has fallen below the minimum threshold required for survival, posing a risk of exit from the market (curve between B and C in subfigure (c)). In such scenarios, even though implementing a high degree of digital transformation could significantly improve profits (point D in subfigure (c)). This option carries an exit risk, making the choice to increase sales and thereby profits potentially infeasible. In these circumstances, firms lose their agency to choose, and the optimal strategy devolves to minimizing or entirely avoiding digital transformation (point A in subfigure (c)).

2.4.7. Robustness Test

To ensure the robustness of the model and simulation, this paper conducted a detailed heterogeneity test on the core variables.

In addition to the text analysis methods employed in the main body of this paper, there may exist potential bias in using weighted keywords from China's government documents. Therefore, in the robustness check, the TF-IDF method was shifted to an equal-weighted approach. The robustness test then recalculated the degree of digital transformation for firms. The results proved to be robust, with the detailed descriptive statistics available in appendix A.

The checks also estimated the impact of digital transformation on capital efficiency and labour efficiency with δ used in main body and with alternative measure of δ. By comparing the relative magnitudes of the two estimated coefficients, the results remained robust across different textual analysis methodologies. The details are stated in Appendix B.

Besides, appendix C repeated the calibration and simulation processes, testing the impact of digital transformation on firm profits under varying market price indices, wage levels, and degrees of market competition. Although the conditions for turning points and their locations varied, the outcomes were consistent with our analysis and discussions. See some representative values of the simulation, please see Appendix C.

2.5. Conclusions

This paper has developed a general equilibrium model based on the Melitz model, considering the heterogeneous effects of digital transformation on firms' capital and labour efficiencies. This model examines how digital transformation influences firms' production strategies and profits, and further discusses the heterogeneity of optimal digital strategies for firms in export markets of varying competitive intensities.

The key contributions of this paper are threefold:

First, while the existing literature has reported the impact of digital transformation on export performance, these discussions have largely been empirical. This model addresses this gap by providing a detailed model construction and theoretical analysis of how digital transformation affects firms' export performance and profits.

Second, this paper has differentiated the heterogeneous impacts of digital transformation on capital and labour efficiencies in production, discussing the optimal pathway for input ratios before and after digital transformation.

Lastly, this paper has examined the heterogeneity of optimal digital transformation strategies for firms in different export market environments. Overall, while digital transformation can positively affect firm profits, excessive digitalization is not the optimal strategy in low-competition markets, and moderate digital transformation is the least desirable in high-competition markets.

Unavoidably, the study has a few limitations. Firstly, aside from capital and labour, there are other production inputs in a firm's production process affected by digital transformation, which also exhibit heterogeneity. Although our CES production function can easily extend to multiple types of inputs, this paper did not delve into scenarios with more than two inputs due to model complexity and comprehensibility. Secondly, due to the late development and immature state of macroeconomic and market data in China, some parameters could not be directly calibrated using Chinese market data. Future simulations could yield more accurate results as the disclosure and maturity of China's market data improve.

Overall, this study finds that digital transformation can be a double-edged sword, not always yielding higher profits in certain market environments. This partially explains why many firms have not achieved the expected results despite undergoing digital transformation. On the other hand, the findings offer theoretical and practical insights for firms considering or already undertaking digital transformation.

2.6. Appendix of Chapter 2

Appendix A. Alternative Measurement of Digital Transformation

This paper employed textual analysis of listed companies' annual reports to estimate the extent of their digital transformation. The empirical estimation methodology relies on an analysis of word frequency in annual reports, the Chinese government's interpretation of digital transformation, and the TF-IDF algorithm. However, as with all studies using textual analysis (Bryzgalova et al., 2023; Grootendorst, 2022; Hoberg & Phillips, 2016; Huang et al., 2023), this method may be biased due to the inappropriate weighting of keywords. To address this concern, this section recalculated the degree of digital transformation using an alternative approach.

Specifically, this part further treated all digital transformation-related terms with equal weight and then recalculated cumulative word frequencies. This approach helps to mitigate the issue of keyword weighting unduly emphasizing the relevance of specific words to digital transformation. The table below presents the descriptive statistics of the digital transformation variable delta using both the main and alternative methodologies, as well as the correlation between these variables, shown in Table A1:

Table A1. Comparison of δ between main and alternative methodologies

Year	Mean (Main)	Mean (Alternative)	Median (Main)	Median (Alternative)	SD (Main)	SD (Alternative)	Correlation
2010	0.121	0.131	0.261	0.050	0.272	0.261	0.858
2011	0.146	0.163	0.298	0.050	0.309	0.298	0.880
2012	0.164	0.179	0.322	0.074	0.329	0.322	0.890
2013	0.193	0.207	0.357	0.086	0.363	0.357	0.895
2014	0.232	0.242	0.386	0.098	0.403	0.386	0.920
2015	0.310	0.308	0.429	0.144	0.478	0.429	0.928
2016	0.383	0.377	0.481	0.211	0.544	0.481	0.936
2017	0.469	0.444	0.523	0.253	0.605	0.523	0.929
2018	0.562	0.522	0.582	0.314	0.677	0.582	0.933
2019	0.652	0.576	0.604	0.372	0.714	0.604	0.922
2020	0.813	0.648	0.630	0.446	0.804	0.630	0.916
Total	0.415	0.383	0.155	0.189	0.609	0.516	0.928

Comparing the results, the figures show measurement approaches yield similar descriptive statistics annually and overall. The correlation coefficients for most years are close to or exceed 0.9, indicating minimal differences between the two weighting strategies. This suggests that the measures are robust across different weighting approaches, maintaining the stability of the indicators. In the subsequent appendix related to empirical analysis, this paper also used alternative measurement of digital transformation to estimate the effect of (δ) to the labour efficiency and capital efficiency of the firms.

Appendix B. Estimation of Capital Efficiency and Labour Efficiency

In the main body of the paper, the empirical results for the impact of corporate digital transformation on capital efficiency and labour efficiency are briefly presented as the parameter estimation results. The data for these estimations were sourced from the annual reports of Chinese-listed companies from 2010 to 2020. Data on digital transformation were derived from text analysis of these annual reports. In terms of firm samples, the listed companies in China are selected as the primary data source. Considering the model focuses on established product- or service-oriented firms that undergo digital transformation than with born-digital firms, thus we only keep the firms in the manufactory industry. Then, we dropped the firms that are under special risk treatment by the China Securities Regulatory Commission. Finally, we dropped the observations with missing variables; the descriptive statistics used in the regression are shown in Table B1.

Table B1. Summary statistics

Variable	Obs	Mean	Std. dev.	Min	Max
CapitalE	16189	0.566	0.281	0.209	1.097
LabourE	16189	10.898	6.640	3.889	24.771
Digital	16189	0.415	0.609	0.000	4.954
Size	16189	22.023	1.049	20.574	23.838
Leverage	16189	0.419	0.191	0.142	0.720
ROA	16189	0.047	0.037	-0.002	0.113
Growth	16189	0.130	0.216	-0.186	0.525
Indep	16189	0.370	0.041	0.333	0.429
BM	16189	0.836	0.612	0.210	2.124
PB	16189	3.368	1.992	1.144	7.380
Firmage	16189	2.861	0.280	2.398	3.258
Top1	16189	0.339	0.128	0.164	0.551
TotalLiabilities	16189	3.203	4.125	0.164	13.020
CurrentLiabilities	16189	2.413	3.001	0.142	9.520

In the equilibrium model, the impact of digital transformation (δ) on capital efficiency (α) and labour efficiency (β) is in linear style. For such a linear model, this paper uses the panel data and then employs a fixed-effects model for estimation. The estimation equation is as follows:

$$\begin{aligned} CapE_{it} &= \phi_1 + \beta_1 \cdot Digital_{it} + \beta_c \cdot Control_{it} + \alpha_i + \gamma_t + \epsilon_{it} \\ LabourE_{it} &= \phi_2 + \beta_2 \cdot Digital_{it} + \beta_c \cdot Control_{it} + \alpha_i + \gamma_t + \epsilon_{it} \end{aligned}$$

In this context, $CapE_{it}$ and $LabourE_{it}$ represent the capital efficiency and labour efficiency of the firm i in year t, respectively, while $Digital_{it}$ denotes the degree of digital transformation of the firm i as of year t. The term $Control_{it}$ refers to common control variables, which include firm size, leverage rate, return on assets (ROA), growth rate of main business revenue, firm age, and price-to-book ratio, among others. The variable α_i represents individual fixed effects, and γ_t

denotes time-fixed effects. The regression results utilise robust standard errors clustered at the industry level.

The results of the panel data regression are shown in Table B2.

Table B2. Effects of digital transformation (δ) to capital and labour efficiency

	(1)	(2)	(3)	(4)	(5)	(6)
	CapitalE	*LabourE*	*CapitalE*	*LabourE*	*CapitalE*	*LabourE*
Digital	0.0118	0.0445	0.0314	0.0566	0.0314	0.0566
	(0.361)	(0.220)	(0.022)	(0.174)	(0.011)	(0.040)
Constant	0.00299	0.0404	2.376	1.535	2.376	1.535
	(0.491)	(0.002)	(0.000)	(0.043)	(0.043)	(0.286)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes	Yes	Yes
Robust SE	No	No	No	No	Yes	Yes
Adjusted R^2	0.824	0.302	0.832	0.299	0.832	0.299
N	16189	16189	16189	16189	16189	16189

p-value are presented in parentheses

The regression results demonstrate that, after controlling for common firm variables, the estimated values of the coefficients ϕ_1, β_1, ϕ_2, and β_2 remain no significant difference and are statistically significant at the 0.05 level (columns (3), (4), (5), and (6)). This makes it capable of pinning down the parameter values in equation (11). Subsequently, as mentioned in Appendix A, an alternative measurement for digital transformation was employed with an equal-weighted text analysis algorithm and conducted an extra set of coefficient estimations as the robustness check, the results of using equal weighted alternative δ are shown in Table B3.

Table B3. Effects of alternative δ to capital and labour efficiency

	(1)	(2)	(3)	(4)	(5)	(6)
	CapitalE	*LabourE*	*CapitalE*	*LabourE*	*CapitalE*	*LabourE*
Digital (Alt.)	0.00519	0.0196	0.0138	0.0249	0.0138	0.0249
	(0.361)	(0.220)	(0.022)	(0.174)	(0.011)	(0.040)
Constant	-0.00383	0.0147	2.357	1.502	2.357	1.502
	(0.535)	(0.300)	(0.000)	(0.046)	(0.045)	(0.291)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes	Yes	Yes
Robust SE	No	No	No	No	Yes	Yes
Adjusted R^2	0.824	0.302	0.832	0.299	0.832	0.299
N	16189	16189	16189	16189	16189	16189

p-value is presented in parentheses

As analysed in Section 4.3, the optimal input ratio of production resources for a firm, before implementing digital transformation, depends on ϕ_1/ϕ_2. With an increase in the degree of digital transformation, it will eventually converge to the relative marginal impacts of δ on capital efficiency and labour efficiency β_1/β_2. Therefore, in the parameter calibration process for this section, the focus is on the relative magnitudes. The coefficients of digital transformation on capital efficiency and labour efficiency, estimated using both weighted and equal-weight methodologies, are shown in Table B4.

Table B4. Comparison of parameters via two methods

	ϕ_1	ϕ_2	ϕ_1/ϕ_2	β_1	β_2	β_1/β_2
Weighted δ	2.376	1.535	1.548	0.031	0.057	0.555
Alternative δ	2.357	1.502	1.569	0.014	0.025	0.554

The comparison of the regression results in Table B4 and estimated coefficients in Table B3 reveals that, despite differences in estimated coefficients, there is no significant variance in statistical significance and the ratios of ϕ_1/ϕ_2 and β_1/β_2.

Appendix C. Variations of Parameters

In the previous analysis, the paper discussed the changes in key indicators for firms under three typical market competition intensities with digital transformation. However, given the complexity and variability of markets that firms encounter, these three scenarios do not comprehensively cover all possibilities. Consequently, this section further refined the range of values for the parameter ε. From historical estimations, the competitive distribution of markets faced by exporting firms lies between 0 and 8. The primary analysis already covered market competition intensities of $\varepsilon = 2, \varepsilon = 4$ and $\varepsilon = 6$. Here the range now is extended to include scenarios where firms face market competition intensities of 1, 3, 5, and 7. The specific results are illustrated in Figure C1, Figure C2, Figure C3, and Figure C4. These results show that after simulating more detailed market competition circumstances, changes in a firm's selling price, volume, and profit with digital transformation are consistent with our analysis.

Notably, when firms face very low competition, they lack the incentive to incur additional costs for implementing digital transformation, a scenario applicable to highly monopolized product markets. However, regardless of how market competition varies, as long as the capital price (p_c) and wage level (w) remain constant, the optimal ratio of production input for firms does not change.

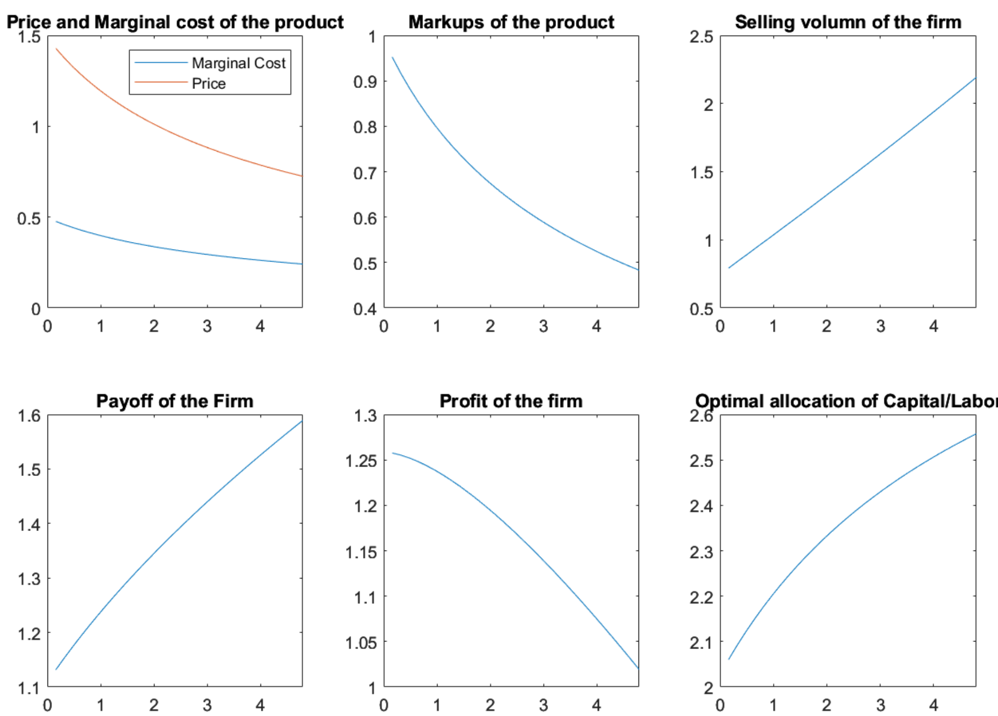


Figure C1. Price, Selling volume and profit of the firm ($\boldsymbol{\varepsilon = 1}$)

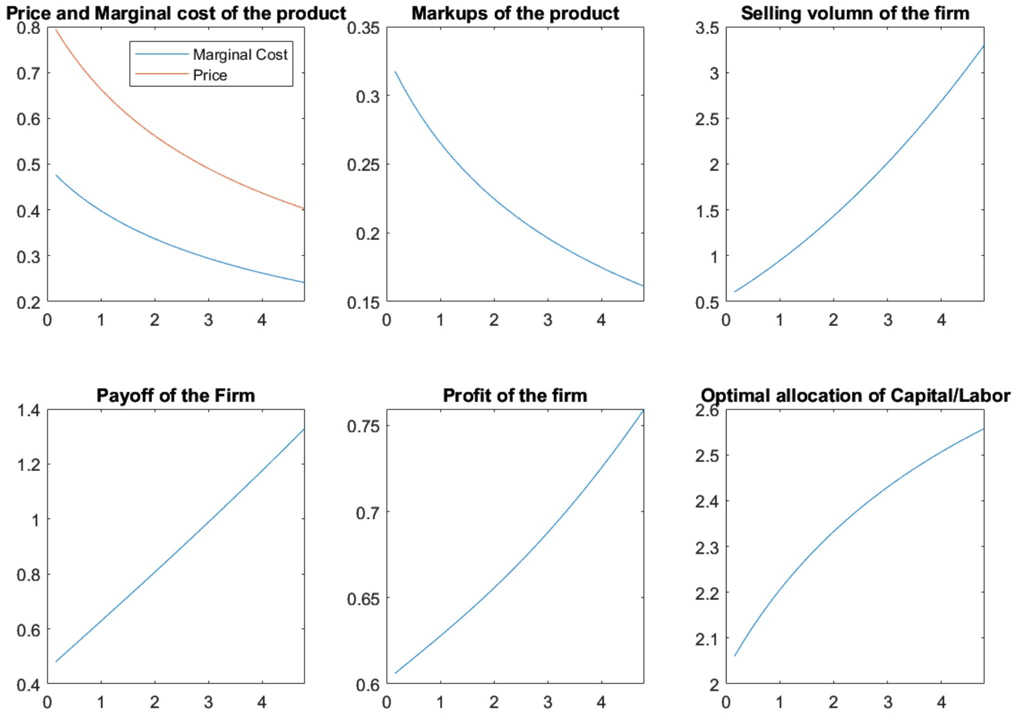


Figure C2. Price, Selling volume and profit of the firm ($\varepsilon = 3$)

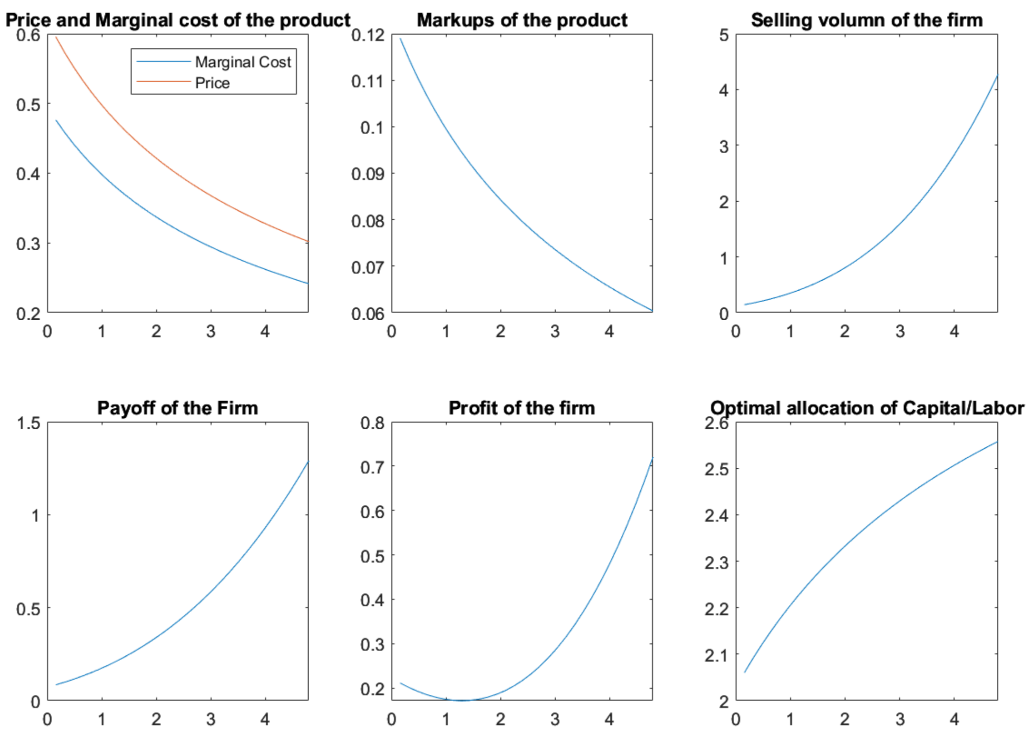


Figure C3. Price, Selling volume and profit of the firm ($\varepsilon = 5$)

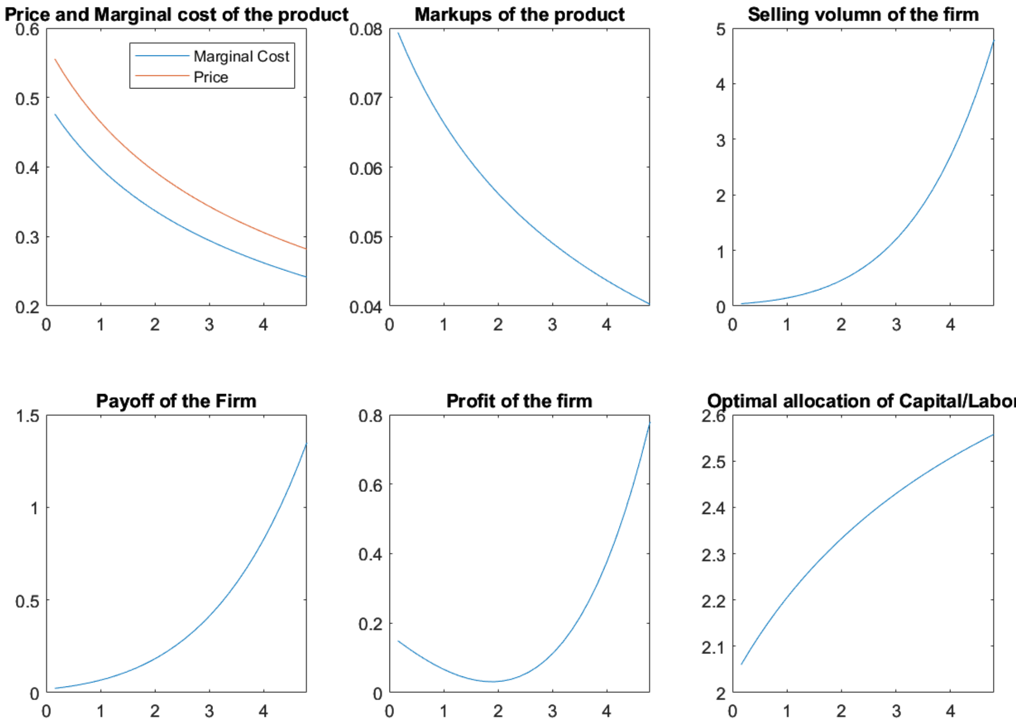


Figure C4. Price, Selling volume and profit of the firm ($\varepsilon = 7$)

Furthermore, the analysis in this extension also tested the optimal allocation between capital and labour for firms under different capital prices and wage rates. Specifically, this part examined the effects of increases and decreases in capital price and wage rate on the optimal allocation ratio. The results indicate that, firstly, as wages rise, the proportion of capital in the optimal allocation ratio increases; conversely, as capital price rises, the proportion of capital in the optimal allocation decreases. This is in line with fundamental economic principles. Secondly, the impact pattern of digital transformation on this ratio does not change with variations in p_c and w. These two points confirm that in economic environments with different price and wage levels, the main conclusion regarding the impact of digital transformation on a firm's capital and labour remains robust. As shown in Figure C5.

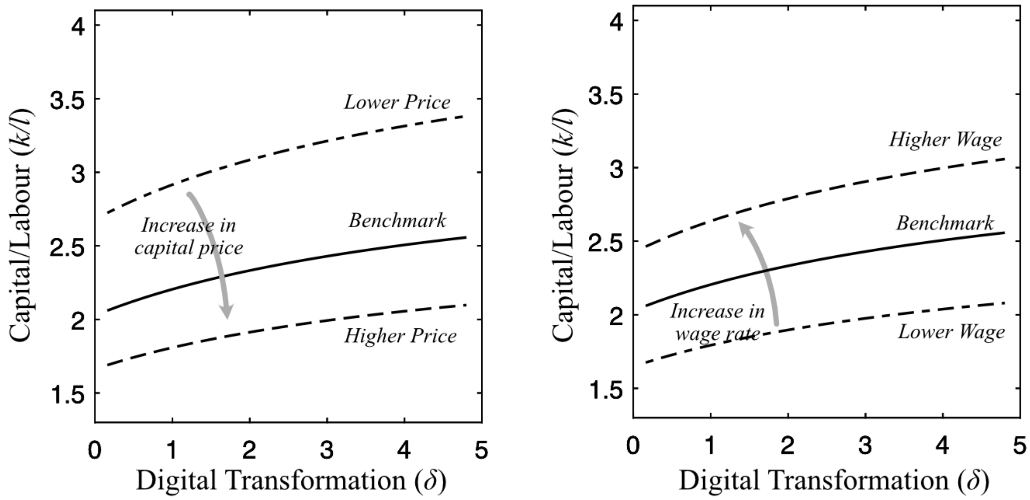


Figure C5. Capital labour allocation under price and wage variations

Chapter 3: Enhancing Export Performance through Digital Transformation: The Roles of Capital and Labour Efficiency

Abstract

This study examines the impact of digital transformation on firms' export performance and the underlying mechanisms. A novel measurement method for digital transformation, based on text analysis, is introduced. Using the Firm-Specific Advantages (FSAs) theory and an extended heterogeneous firm model, empirical results reveal a significant positive effect of digital transformation on export performance, primarily through improvements in capital and labour efficiency. These findings align with the FSAs theory's summarisation of technology and human capital advantages in the digital era.

Mediation tests show that capital efficiency is a robust mechanism, while labour efficiency's impact is less consistent. Heterogeneity analysis indicates that labour efficiency improvements are more effective in firms with initially low labour efficiency. Furthermore, when capital and labour efficiency development is imbalanced, focusing digital transformation efforts on the relatively weaker one yields more significant benefits. This supports the optimal transformation allocation theory proposed in Chapter 2.

The robustness tests, including alternative variables and methods, as well as instrument variables, confirm the reliability of the results. This research contributes by developing a novel measurement of digital transformation, validating the mechanisms enhancing export performance. The paper also highlights the importance of balanced efficiency improvements. The findings suggest that firms must carefully allocate resources during digital transformation to maximise benefits.

Keywords: Digital Transformation; Export Performance; Capital Efficiency; Labour Efficiency; Firm-Specific Advantages

3.1. Introduction

The digital economy has experienced rapid development in recent years, with new concepts such as the Internet of Things (IoT), artificial intelligence (AI), digital platforms, and smart manufacturing becoming widely recognized (Calderon-Monge & Ribeiro-Soriano, 2023; Graetz & Michaels, 2018; Na et al., 2022; B. Zhang et al., 2024). These technologies are increasingly being adopted by public sectors, businesses, and individuals (Finkelstein Shapiro & Mandelman, 2021; Jahanmir & Cavadas, 2018; Molinillo & Japutra, 2017; Skare & Riberio Soriano, 2021). At the enterprise level, the integration of these new technologies is referred to as digital transformation, which plays a pivotal role in fostering the development of the digital economy (Feliciano-Cestero et al., 2023; Verhoef et al., 2021).

As digital transformation continues to be implemented in practice, it has garnered significant attention from the academic community. Current academic research on digital transformation can be broadly categorized into qualitative and quantitative studies (Hanelt et al., 2021).

In qualitative research, scholars often derive interpretations from industry practices, exploring successful cases, and analysing the motivations and specific implementation paths of applying transformations (Bongiorno et al., 2018; Elia et al., 2021; Horlacher & Hess, 2016). One of the earliest studies on digital transformation can be traced back to (Westerman et al., 2011). This report discussed the distinctions between digital transformation and traditional technological upgrades, outlined the necessary elements for successful digital transformation, and proposed methods for assessing a firm's degree of digital maturity (Westerman et al., 2011). Subsequent research has largely followed this direction but has delved into more specific areas (Gong & Ribiere, 2021; Kraus et al., 2021; Rachinger et al., 2018; Reis et al., 2018; Vial, 2019; Zhai et al., 2022). For example, some studies emphasise the importance of information in digital transformation (Clemons, 2019), others focus on how management drives and adapts to digital transformation and adjusts management practices (Bongiorno et al., 2018), while some explore strategies for large traditional businesses to simultaneously transform their existing operations and develop new digital ventures (Wiraeus & Creelman, 2019).

One branch of qualitative research is the Firm Specific Advantages (FSAs) theory in the digital era, developed by (Banalieva & Dhanaraj, 2019). Their work provided a clear implementation motivation and path for corporate digital transformation under the framework of

FSAs in the digital age. Firms need to maintain their FSAs to remain competitive and profitable in international trade (Adarkwah & Malonæs, 2022; Aharoni, 1993; Birkinshaw et al., 1998; I. H. Lee & Rugman, 2012; Yaprak et al., 2018). In the digital age, FSAs are divided into technology advantage and human capital advantage, forming the specific needs of firms (Banalieva & Dhanaraj, 2019). The theoretical model derived in Chapter 2 suggests that digital transformation can significantly improve a firm's capital efficiency and labour efficiency, aligning perfectly with the two core demands of FSAs, thereby enhancing export performance.

Conversely, quantitative research often focuses on measuring digital transformation, its impact on firms, and the economic consequences for the surrounding environment (Acemoglu & Restrepo, 2018a, 2018b; Dinlersoz & Wolf, 2023; F. Wang et al., 2023; F. Wang & Ye, 2023; Wu et al., 2022; Yue, 2023). For example, studies have examined the effects of digital transformation on a firm's innovation capability, financing costs, stock performance, and the infrastructure level of surrounding communities (J. Li et al., 2022; Llopis-Albert et al., 2021; Verhoef et al., 2021). Furthermore, analysing the effects of digital transformation solely within a firm's domestic market is not sufficiently comprehensive, especially for high-performing companies (Bustos, 2011; Das et al., 2007; Melitz & Redding, 2014). For these enterprises, expansion into international markets is critically important for enhancing profits, increasing market share, and reducing risks (Greenaway & Kneller, 2007; Wagner, 2007). However, there is a notable scarcity of academic research on digital transformation in the context of international business (F. Wang et al., 2023; F. Wang & Ye, 2023).

Therefore, based on the FSAs theory and the general equilibrium theory under digital transformation developed in Chapter 2, this study investigates whether digital transformation can enhance capital efficiency and labour efficiency, thereby meeting the FSAs requirements in the digital era and ultimately improving export performance. The illustrated alignment between FSAs in the digital era and digital transformation is shown in Figure 9.

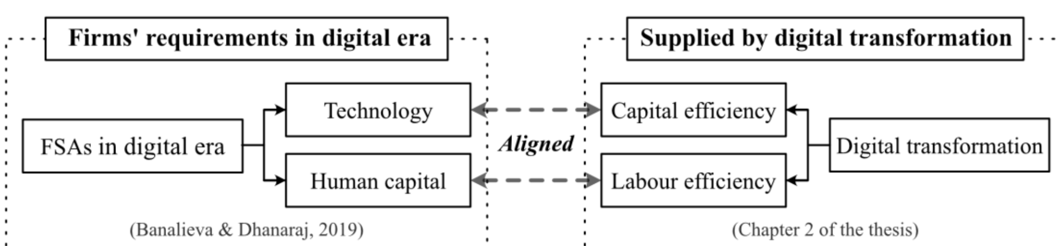


Figure 9. The associations between FSAs and digital transformation

The content of this study is divided into four main parts. First, it connects the requirements of firm-specific advantages in the digital age with the effects of digital transformation, bridging the gap between transformation needs and effects. Second, leveraging natural language processing techniques, this study develops a new measurement method for digital transformation based on the text analysis of corporate annual reports. Third, the study examines the internal mechanisms through which digital transformation affects export performance and explores the applicability of capital and labour efficiency mechanisms. Finally, robustness tests are conducted, including a novel instrumental variable for digital transformation based on geographic information.

The study's key contribution can be concluded in four aspects: First, it uses text analysis techniques to develop a novel measurement approach to the degree of digital transformation in firms. Second, it empirically tests the effect of digital transformation on export performance, mechanisms, and heterogeneity among firms. Third, the findings support the proposed perspective in Chapter 2 that digital transformation is not beneficial to all firms in all conditions. Firms must compare the cost and revenue of digital transformation and allocate the resources carefully. Lastly, this paper introduces an innovative instrument variable by combining firm-level geographical information and digital development trends in the macro scope.

3.2. Theoretical Background and Hypothesis Development

3.2.1. Firm-Specific Advantages in the Digital Era

A firm's successful international entry and operation abroad requires unique resource and capability bundles (Verbeke & Yuan, 2024). Traditional metrics for evaluating firms, such as the scale of fixed assets and number of employees, no longer determine success in today's economic environment (Banalieva & Dhanaraj, 2019; Feliciano-Cestero et al., 2023). In recent years, the rapid advancement of computer technology has led to the emergence of new technologies, devices, and services on a global scale, fundamentally transforming business processes, commercial logic, and core competencies (Calderon-Monge & Ribeiro-Soriano, 2023; Verhoef et al., 2021; Wessel et al., 2021). In an era characterized by highly developed digital technologies and intensified competition among firms, there is an increased emphasis on cost control and efficiency improvements (W. Li & Li, 2022). To survive or maintain profitability in this environment, firms must develop new competitive advantages, which may stem from superior technological capabilities or enhanced employee collaboration. These unique resources and capabilities are called Firm-Specific Advantages (FSAs) (Aharoni, 1993; Birkinshaw et al., 1998).

Historically, various advantages have been defined by academia as FSAs, including proprietary assets, organisational capabilities, and relational resources (Bhaumik et al., 2016; Chiao et al., 2006; Erramilli et al., 1997). These theories are based on the specific economic conditions and periods in which firms operate, analysing the core strengths of firms and how to maximise the benefits derived from these strengths (Sun & Lee, 2019). For instance, some studies emphasise capital and financial resources as sources of a firm's FSAs, detailing firms' advantages and strategies (Kedia et al., 2012; Le & Lei, 2018; I. H. Lee & Rugman, 2012). Furthermore, the impact of organisational capabilities as a core FSA on firms is discussed (Cuervo-Cazurra et al., 2018; Hennart et al., 2017; Sun & Lee, 2019). These studies abstract a firm's competitive advantages into several unique dimensions and explore how firms can transform their production and management models to maximise the utilization of these advantages.

As discussed in the literature, FSAs evolve significantly with changes in the era and economic environment in which a firm operates (Birkinshaw et al., 1998; Chiao et al., 2006; Erramilli et al., 1997). In the digital economy era, previously discussed FSAs have become out-dated (Banalieva & Dhanaraj, 2019; Feliciano-Cestero et al., 2023). Rapid technological development has acted as a trigger, causing substantial changes in core FSAs. Banalieva and Dhanaraj suggests that while different dimensions of a firm's FSAs interact in the long term, they can be decomposed into distinct dimensions in the short term (Ando & Fisher, 1963; Banalieva & Dhanaraj, 2019; Simon, 1994). Within the context of the digital era, FSAs can primarily be categorized into two dimensions: technology and human capital (Banalieva & Dhanaraj, 2019). Specifically, firms need core technologies to maintain their competitive edge, encompassing advancements in production processes and new patents. Regarding human capital, firms require sophisticated workers to effectively utilise new technology. When these two demands are met, production efficiency significantly improves, costs decrease, profits rise, and firms maintain their competitive FSAs in this fast-changing environment (Adarkwah & Malonæs, 2022).

While it is true that technology and human capital have historically been considered core firm-specific advantages (FSAs), the FSAs framework remains uniquely suited to analysing firm competitiveness and export performance in the digital era (Adarkwah & Malonæs, 2022; Banalieva

& Dhanaraj, 2019). The primary rationale for selecting FSAs as the theoretical foundation of this chapter is its explicit emphasis on firm heterogeneity in international competitiveness, which directly aligns with this study's focus on how digital transformation contributes to export performance variations across firms.

In contrast to alternative frameworks, such as the Resource-Based View (RBV) or Dynamic Capabilities Theory, FSAs explicitly captures the interplay between firm-specific resources and international market conditions, making it particularly relevant for analysing export activities. The RBV, while valuable, mainly addresses internal resource endowments and competitive advantage without a direct internationalization context (D. Chen et al., 2022; Schu et al., 2016; Wójcik, 2015). Dynamic Capabilities Theory highlights firms' abilities to adapt and innovate but does not inherently emphasize the international dimension of competitiveness or exports specifically (Buzzao & Rizzi, 2021; Chari et al., 2022; Y. Chen et al., 2022; Teece, 2023).

Moreover, the FSAs concept acquires enhanced relevance in the digital economy context. Although technology and human capital have long been recognized as firm-specific advantages, the nature and intensity of these advantages have significantly evolved. In the digital era, technological capability is characterized by rapid innovation cycles, digital platform integration, and data-driven business models, differentiating itself clearly from traditional technological capabilities. Similarly, human capital advantages now emphasize digital literacy, data analytics expertise, and adaptability to rapidly changing technological environments. Consequently, FSAs theory, which inherently considers such context-specific competitive advantages, provides a robust theoretical lens to analyse how digitalization reshapes the competitive landscape, particularly in international markets.

Therefore, while other theoretical frameworks could offer complementary perspectives, FSAs is selected as the core theoretical foundation due to its unique capability to bridge firm-level digital transformation with international competitiveness and export performance, explicitly accounting for firm heterogeneity, technological evolution, and changing skill requirements in the digital era.

3.2.2. Digital Transformation

Digital transformation, defined as encompassing the adoption of digital technology to fundamentally change business practices, engenders significant shifts in production, management, and governance (Feliciano-Cestero et al., 2023). Its relevance is particularly pronounced in the context of globalisation, where firms compete not just locally but on a global stage (B. Zhang et al., 2024). The potential for digital technologies to streamline operations, enhance product quality, and improve customer engagement is likely to have profound implications on a firm's ability to enter and succeed in new markets (AL-Khatib, 2023; F. Wang et al., 2023; F. Wang & Ye, 2023).

Under this context, digital transformation is a crucial pathway for firms to maintain their FSAs. Firstly, as previously analysed, the primary FSA requirements of firms in this era are technology and human capital. Correspondingly, as analysed in Chapter 2, digital transformation can enhance both capital efficiency and labour efficiency, thereby improving total factor productivity and benefiting firm profits (T. Y. Kim et al., 2018; Melitz, 2003; Nazarko & Chodakowska, 2017). It is important to note that the improvement in capital efficiency through digital transformation is multi-dimensional, encompassing both hardware support, such as better production equipment, and software support, including management systems and employee welfare (Finkelstein Shapiro & Mandelman, 2021; Skare & Riberio Soriano, 2021). These efficiency improvements are based on the development and adoption of modern technology. Similarly, firms need to enhance labour efficiency, which is closely related to their demand for human capital. The improvement in labour efficiency involves training staff and hiring more sophisticated workers (Acemoglu & Restrepo, 2018a, 2018b; Ouma & Premchander, 2022).

In summary, digital transformation can enhance a firm's capital and labour efficiency, meeting its technology and human capital requirements and enabling the firm to maintain its FSAs in the digital economy era.

3.2.3. Hypothesis Development

In the field of international business, discussions on firms' profitability and survival in export activities often highlight the necessity of possessing unique Firm-Specific Advantages (FSAs) (Adarkwah & Malonæs, 2022). Previous studies have indicated that these FSAs vary across different historical stages and economic environments (Bhaumik et al., 2016). In the current era of rapid technological advancement, the core FSAs for firms have shifted to technology advantage and human capital advantage (Banalieva & Dhanaraj, 2019). Consequently, these advantages have become essential for modern exporting firms to enhance export performance.

As discussed in Chapter 2, digital transformation within firms can significantly improve capital efficiency through the adoption of new technologies, aligning with the demand for technology advantage in the digital age (Banalieva & Dhanaraj, 2019). Similarly, digital transformation can enhance labour efficiency by training existing employees or recruiting sophisticated personnel, addressing the need for human capital advantage. This alignment between firms' need for firm-specific advantages and the efficiencies provided by digital transformation suggests a synergistic relationship. Then, from the simulated evidence from Chapter 2, firms could lower the direct and indirect costs in the production and selling process, gaining an easier threshold of entering the export market. Furthermore, the selling volume and the overall profit will increase in most of the market competition cases.

Therefore, we propose the first research hypothesis:

H1: Digital transformation can enhance firms' export performance.

Furthermore, if digital transformation can enhance firms' export performance, exploring the underlying mechanisms driving this improvement is essential. Specifically, the current theoretical framework suggests two potential mechanisms.

First, the enhancement of export performance may stem from increased capital efficiency. Capital efficiency refers to a firm's ability to maximise outputs generated from each unit of input, particularly in terms of fixed and working capital (Ashraf, 2012; Doms, 1996). Digital technologies such as automated manufacturing systems, advanced analytics, and Internet of Things (IoT) applications play a pivotal role in optimising asset usage (Acemoglu & Restrepo, 2018a, 2018b). These technologies enable real-time monitoring and management of assets, leading to more efficient production processes and reduced downtime (Acemoglu & Restrepo, 2018b). Moreover, digital platforms can facilitate better asset allocation, ensuring that capital resources are used more judiciously and effectively (Finkelstein Shapiro & Mandelman, 2021). As discussed in Chapter 2, capital efficiency should be understood broadly, encompassing not only the updating of physical production equipment but also the application of technology across various aspects of a firm's operations, including material tracking devices, project management systems, new employee communication platforms and more (Feliciano-Cestero et al., 2023; Valokivi et al., 2023). These encompass both tangible and intangible assets and systems.

Second, the improvement in export performance could also result from increased labour efficiency. Corresponding to capital efficiency, labour efficiency measures the output per unit of labour input, reflecting how effectively workers utilise these tangible and intangible assets (T. Y. Kim et al., 2018; Ouma & Premchander, 2022). Digital transformation impacts labour efficiency through the automation of routine tasks, enhancement of communication, and by providing tools that aid in better human resource management (Bongiorno et al., 2018). For instance, AI and machine learning can automate repetitive tasks, freeing up employees for higher-value activities that require creative and strategic thinking (Bahoo et al., 2023; Hartmann & Henkel, 2020). Similarly, collaborative tools and platforms enhance productivity by improving communication and reducing the time spent on coordinating tasks (Ben Arfi & Hikkerova, 2021; Frenken & Fuenfschilling, 2020).

The interplay of these two types of efficiency significantly impacts a firm's production and operational efficiency. For instance, a firm with low labour efficiency may not fully leverage advanced digital equipment due to a lack of sophisticated employees, while highly skilled employees may not perform optimally with outdated equipment (Ramesh & Delen, 2021; Saldanha, 2019). Therefore, given the inherent differences between these two efficiencies, it is crucial to examine whether capital efficiency and labour efficiency function as internal mechanisms through which digital transformation affects firms' export performance. To this end, we propose hypotheses H2a and H2b.

H2a: Digital transformation enhances firms' export performance by increasing capital efficiency.

H2b: Digital transformation enhances firms' export performance by increasing labour efficiency.

For the third research hypothesis, we aim to empirically evaluate the theoretical analysis in Chapter 2, which proposes an optimal digital transformation strategy for firms. Specifically, we seek to explore whether the impact of digital transformation on export performance through improvements in capital efficiency and labour efficiency exhibits heterogeneity among firms with imbalanced efficiency improvements. Based on an extended Melitz model considering digital transformation (Melitz, 2003), our general equilibrium model of firm production reveals that there exists an optimal level of digital transformation and resource allocation strategy, as illustrated in

Chapter 2. In brief, when a firm's labour efficiency and capital efficiency are mismatched, focusing digital transformation efforts on the weaker ones will lead to more performance improvements. In contrast, further enhancing the already stronger efficiency may result in insufficient performance gains to offset the rising costs, thus causing more negative impacts on the firm. Based on this analysis, we propose Hypothesis 3:

H3: Digital transformation is not always beneficial, but there exists an optimal transformation strategy.

It is important to note that Hypothesis 3 cannot be validated through a single empirical regression analysis. Instead, it requires a combination of mechanism testing and grouping regression analysis.

By advancing these hypotheses, this research seeks to empirically examine the effect of digital transformation on export performance and its mechanisms. Then this research will also assess the heterogeneity on what conditions digital transformation will benefit to the firm's export performance.

3.3. Research Design

3.3.1. Methodology

Multiple methodologies are employed to construct the research design of this paper.

First, this research conducted a thorough review of academic papers on firm-specific advantages (FSAs) theory and digital transformation with the literature research method (Snyder, 2019). This involved an extensive literature search to understand the concepts and key viewpoints of FSAs theory, identifying the two essential requirements of FSAs in the digital era (Bhaumik et al., 2016; Chiao et al., 2006; Erramilli et al., 1997; I. H. Lee & Rugman, 2012). Additionally, this research explored the origins and development of digital transformation (Fitzgerald, 2014; Vial, 2019), incorporating the general equilibrium model presented in Chapter 2 of the thesis, along with academic discussions and practical applications. The literature analysis revealed two potential effects of digital transformation.

Second, the research used theoretical synthesis to link the advantages required by FSAs theory with the potential impacts of digital transformation, thereby proposing the hypotheses for this paper (Barnett-Page & Thomas, 2009; Eaves, 2001).

Third, for the empirical methodology, this research applied a high-dimensional fixed effects approach to evaluate the proposed hypotheses (Guimarães & Portugal, 2010). In addition to the baseline empirical investigation, mediating and moderating effect models were employed to examine the mechanisms and heterogeneity underlying the association (Fairchild & MacKinnon, 2009). To address potential biases in the epistemology and measurement of core independent and dependent variables, alternative variables were also used to replicate the baseline results (Bloomfield & Fisher, 2019). Furthermore, to mitigate endogeneity issues, this research employed the Generalized Method of Moments (GMM) estimation method and instrumental variables to establish causal relationships between digital transformation and export performance (Berry & Compiani, 2023; Kang & Sivaramakrishnan, 1995; Wooldridge, 2001).

3.3.2. Sample and Data

This research used the quantitative analysis method to examine the hypotheses developed and conducted a series of empirical tests. Firstly, this research tested whether adopting digital transformation significantly impacts a firm's export performance (H1). Secondly, it tested how these two efficiency improvements contributed to total productivity (H2a and H2b). Then, by applying heterogeneity analysis, the research tested whether these mechanisms vary across different firms and whether the optimal digital transformation strategy exists (H3).

In selecting the sample for this study, this research constructed a dataset from publicly listed Chinese companies for two primary reasons. First, the speed and scale of China's digital economy development are exceptionally rapid. According to data from the "China Digital Economy Development Research Report" published by the China Academy of Information and Communications Technology (Zhao et al., 2024), China's digital economy has increasingly asserted its significance within the national economic framework. As illustrated in Figure 10, in 2023, the digital economy accounted for 42.8% of China's GDP, representing a 1.3 percentage point increase from the previous year (W. Cheng et al., 2024; Jia et al., 2024). This growth underscores the emergence of the digital economy as a critical support and major driving force for the nation's economic development (Zhai et al., 2022). In terms of growth rate, the digital economy experienced a nominal year-on-year increase of 7.39% in 2023, surpassing the overall nominal GDP growth rate of 4.64% by 2.76 percentage points. Notably, the expansion of the digital economy contributed 66.45% to the overall GDP growth.

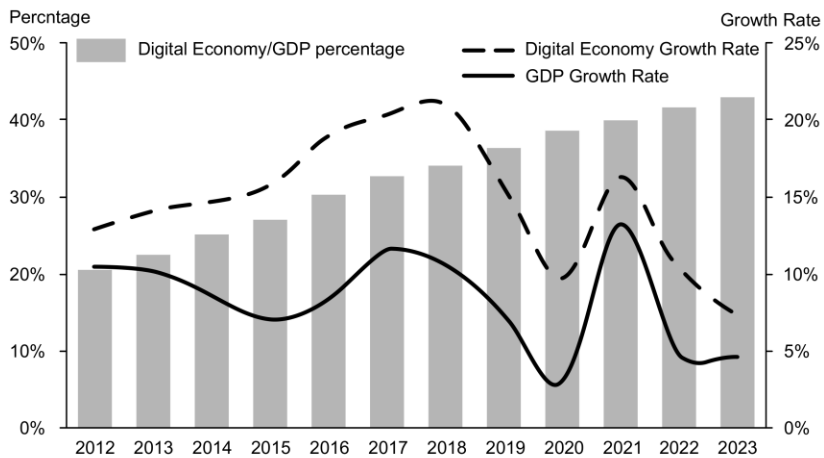


Figure 10. The development of the digital economy in China

Second, in the realm of exports in 2023, China's total import and export value has ranked first in global merchandise trade for seven consecutive years, holding a significant share worldwide (Y. Wang et al., 2024; B. Zhang et al., 2024). Therefore, based on these two considerations, analysing the impact of digital transformation on the exports of Chinese enterprises is highly representative and pertinent.

The empirical tests encompass all companies listed on the A-shares market from 2010 to 2016. Given the distinct business models and profit mechanisms between financial sector firms and traditional sectors such as agriculture, manufacturing, and services, firms categorized under the financial industry by the China Securities Regulatory Commission were initially excluded from the sample. Additionally, to mitigate the influence of firms with irregular financial or operational conditions, which have been subject to special treatment by the China Securities Regulatory Commission since 1998, companies labelled as "ST" were also omitted. Lastly, firms with missing key data were removed, resulting in a final tally of 9682 firm-year observations.

The core variables for this analysis were derived from multiple sources. The primary measure of a firm's degree of digital transformation was obtained through textual analysis of disclosures made by listed companies. Complementarily, financial metrics were sourced from the annual reports of these companies and the CSMAR database, which is renowned for its comprehensive and authoritative coverage of financial information on Chinese-listed firms.

It is important to acknowledge sample selection bias in this study. Our final dataset comprises 9,682 firm-year observations from publicly listed companies, which represent around 46% of all valid listed firms, and only a small fraction of all Chinese enterprises. Generally, listed firms tend to be larger, more regulated, and potentially further along in their digital transformation journeys compared to the non-listed firms. Consequently, the extrapolation of our findings to small or medium-sized enterprises (SMEs) or non-listed firms requires extra caution. Despite these limitations, publicly available custom export and annual reports data of listed firms make this sample the most feasible approach for our study's in-depth analysis.

3.3.3. Dependent Variables

Export Performance

In the study of firm exports, a primary focus is on export performance, with export value being the most commonly used proxy indicator in existing literature. Theoretically, Melitz emphasises in his heterogeneous firm trade model that export value plays a crucial role in reflecting a firm's market share and competitiveness, where higher export values generally indicate significant global market competitiveness (Melitz, 2003). Empirically, Bernard finds a positive correlation between export value and firm productivity, wage levels, and firm size, further establishing export value as an important tool for assessing international market performance and economic benefits (Bernard et al., 2007). Helpman validate the effectiveness of export value through their trade flow model, suggesting that export value not only measures firm performance across different markets but also provides critical insights for trade policy analysis (Helpman et al., 2008). Greenaway and Kneller explore the relationship between firm heterogeneity and export behaviour, discovering that high-productivity firms have significantly higher export values than low-productivity firms, reinforcing the notion that export value is a key indicator of international performance (Greenaway & Kneller, 2007). Wagner supports this view in his review, noting a significant positive association between export value and firm productivity, with exporting firms generally exhibiting higher productivity levels (Wagner, 2007). Collectively, these studies indicate that export value is not only a direct reflection of economic gains from international trade but also a vital standard for evaluating a firm's international competitiveness and market share.

Based on this literature review, we use the aggregated export value across different countries and trade methods for listed firms as the proxy indicator for export performance in this study.

Specifically, this variable represents the total amount of products a firm exports to various countries through different trade methods over a certain period. Notably, all export value data for the firm-year observations are converted to USD based on historical exchange rates to mitigate the impact of exchange rate fluctuations, thereby enhancing data comparability and accuracy.

Capital Efficiency

Capital Efficiency is defined and quantified through the metric of capital turnover, which measures a firm's efficiency in generating sales revenue from its total assets (Doms, 1996; Meles et al., 2016). Specifically, this ratio indicates the amount of sales income produced per unit of total assets employed. Compared to Return on Assets (ROA), capital turnover provides a more precise assessment of a firm's capital efficiency. This distinction is crucial as capital turnover focuses solely on the productive use of assets in generating sales, thereby offering a direct evaluation of asset utilization efficiency independent of profitability metrics such as net income.

Labour Efficiency

Labour Efficiency is operationalized as the ratio of sales revenue to wage expenses. This measure effectively captures how efficiently a company utilises its labour resources, quantifying the amount of sales generated for every unit of wage expenditure (Tran & Vo, 2020). This metric emphasises the productivity of labour by directly linking payroll costs to the revenue outcomes, providing a focused insight into the economic effectiveness of the workforce investment (T. Y. Kim et al., 2018; Mallick, 2012; Nazarko & Chodakowska, 2017; Ouma & Premchander, 2022).

The measurement of capital and labour efficiency here is consistent with the corresponding definitions in Chapter 2's model.

3.3.4. Independent Variable: Digital Transformation

There is no unified standard for measuring the degree of digital transformation in firms. Unlike traditional technological progress, digital transformation encompasses multiple dimensions of a firm's operations, including production and management. Therefore, identifying a reliable measurement and proxy variable is crucial, as the method used to estimate these proxy variables directly impacts the credibility of empirical results.

Existing literature on measuring digital transformation in firms can be categorized into three primary methods. The first method involves indirect measurement, using lower-granularity indicators to gauge a firm's digital transformation. For example, Abeliansky and Hilbert use the digital development level of the city where the firm is located as a proxy for the firm's digital transformation level (Abeliansky & Hilbert, 2017). While this method is straightforward, it has significant drawbacks (F. Wang & Ye, 2023). The digital development level of a city may correlate with a firm's degree of digital transformation, but it does not guarantee it, leading to substantial measurement bias (Yue, 2023). Moreover, this method lacks differentiation at the firm level within the same city (Combes et al., 2012).

The second method is the classification approach. This method abstracts digital transformation into a dummy variable or a 5-scale Likert scale based on interviews and surveys to determine whether a firm is undertaking digital transformation (Alsheibani et al., 2018; Bharadwaj et al., 2013; Denicolai et al., 2021; F. Li et al., 2016). Although this method is more accurate than regional proxies and allows for differentiation among firms within the same area, it only indicates whether a firm has initiated digital transformation without capturing the degree of transformation. Thus, it cannot effectively distinguish between firms that have only begun basic digital transformation and those that have comprehensively implemented it.

The third method constructs measurement indices based on text data related to digital transformation from firms' annual reports, announcements, and news articles (Hoberg & Phillips, 2016; Mehl, 2006). This approach involves analysing the frequency of relevant keywords to develop an indicator of the degree of digital transformation. This method has rapidly advanced in recent years, creating a robust evaluation system and offering greater accuracy and representativeness than previous methods.

Despite the advantages of text analysis-based methods, they exhibit two primary shortcomings. Firstly, the selection of keywords is subjective. Existing literature often defines a keyword list for frequency counting, but the dynamic nature of digital technology means that variations in this list can significantly affect the resulting digital transformation indicators (Brysbaert et al., 2018). Secondly, the keywords lack weighted relevance. Although all keywords may be somewhat related to digital transformation, their relevance varies (Arefyev et al., 2018; Corrêa & Amancio, 2019). For instance, the terms "smart factory" and "internet platform" both indicate actions toward digital transformation, but a firm implementing a smart factory has likely adopted a higher degree of transformation than one just completing an internet platform. Therefore, it is essential to assign different weights to keywords based on their association with digital transformation (Mikolov et al., 2013; Pelevina et al., 2017).

Building on the review of digital transformation measurement methods (Calderon-Monge & Ribeiro-Soriano, 2023; Feliciano-Cestero et al., 2023; F. Wang & Ye, 2023; Y. Wang et al., 2024; Yue, 2023; B. Zhang et al., 2024), this study proposes a new metric based on the textual analysis of corporate annual reports. By optimizing keyword selection and incorporating different weights for these keywords, we have developed a refined measurement of digital transformation. This metric is constructed at the firm-year level, ensuring granular detail and moving beyond simple classification to capture a more nuanced degree of transformation.

The process for obtaining the digital transformation metric involves several steps. First, we used a Python web scraping program to download annual report PDFs from the information disclosure pages of the Shanghai and Shenzhen Stock Exchanges. Second, we extracted the text from these reports using Python. For reports that could not be processed programmatically, we manually supplemented the text extraction. After obtaining the textual data, we selected relevant keywords and their weights from the "White Paper on Digital Transformation of Enterprises" published by the Chinese government. This white paper, authored by leading national research institutions such as the National Information Technology Standardization Technical Committee's Big Data Standards Working Group and the China Electronics Standardization Institute, provides a comprehensive study on digital transformation development.

We chose this document as the benchmark for keyword selection and weighting for several reasons. Firstly, previous studies have provided keyword lists for digital development, but these lists are constructed in an English context and are not applicable to the Chinese context. Secondly, compared to other economies, the Chinese government exerts significant political and economic influence on enterprises. The terminology and core concepts in government documents have a substantial impact on corporate strategies and the language used in annual reports (Gordon & Li, 1991; Z. Tang & Tang, 2016; Zhao et al., 2015). Lastly, the white paper offers detailed descriptions of the directions, pathways, and key concepts of digital transformation in China, which serve as crucial references for assigning weights to the keywords.

In conclusion, using the "White Paper on Digital Transformation of Enterprises" as our benchmark for determining the scope and weights of keywords ensures high accuracy within the current Chinese context.

It is important to note that the weights of keywords derived from the white paper are universal across all firms and do not account for the specific industry or business characteristics of each company. For example, the keyword "5G," while closely associated with digital transformation, might merely describe the core business of a telecommunications equipment company rather than indicate genuine digital transformation. Therefore, when determining keyword weights for each firm, it is essential to consider not only the strength of the keyword's association with digital transformation but also its relevance to the firm's specific business. For instance, for a company manufacturing 5G communication equipment, the weight of the keyword "5G" should be adjusted downward to avoid overestimating its degree of digital transformation. To address this issue, we must add another layer of weight to capture the heterogeneity among firms. Thus, this part introduced the TF-IDF algorithm to adjust the weights (Bafna et al., 2016).

TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical method used in text analysis to evaluate the importance of a word within a document set or corpus (Bafna et al., 2016; Fan & Qin, 2018; C. Liu et al., 2018). It combines term frequency (TF) and inverse document frequency (IDF). Specifically, TF refers to the frequency of a word in a specific document, reflecting the word's importance in that document. The formula is:

$$TF(t,d) = \frac{Frequency\ of\ term\ t\ in\ document\ d}{Total\ number\ of\ terms\ in\ document\ d}$$

Inverse document frequency (IDF) measures the rarity or commonness of a word across the entire document set. The fewer documents a term appears in, the higher its IDF value, indicating its greater importance in distinguishing documents. The formula is:

$$IDF(t,D) = log\left(\frac{Total\ number\ of\ documents\ N}{Number\ of\ documents\ containing\ term\ t}\right)$$

By combining TF and IDF, we can obtain a score representing the importance of a term within a document. The formula is:

$$TF\text{-}IDF(t,d,D) = TF(t,d) \times IDF(t,D)$$

For example, although the keyword "5G" has a high term frequency (TF) in the annual reports of telecommunications equipment manufacturers, its low IDF within the industry results in a lower adjusted weight compared to the benchmark. Conversely, the keyword "5G" in the annual report of an agricultural firm would have a lower TF but a higher IDF, leading to a higher adjusted weight than the benchmark. Thus, the introduction of the TF-IDF algorithm ensures that our keyword frequency indicator more accurately captures the degree of digital transformation.

In summary, the whole weights of keywords related to digital transformation consists of two parts. The first part comes from the Chinese government document, reflecting the importance of the keywords according to the government report, and universal to all firms. The second part captures the characteristics of each firm, using TF-IDF algorithm to dynamically adjust the weights based on their word frequency in the whole annual report document. It is important to note that though the introduction of TF-IDF algorithm could mitigate the weight bias of the key words by considering the characteristics of the firms, this method still cannot remove all the bias factors.

After determining the keywords related to digital transformation and adjusting their weights using the TF-IDF algorithm, we return to the annual report text data of listed firms. We search for each keyword within the annual reports, calculate their frequencies, and multiply these frequencies by the adjusted TF-IDF weights.

Another important detail is that our measurement of a firm's digital transformation for each year is incremental. The overall degree of a firm's digital transformation accumulates over time. For instance, if a firm completes the implementation of an Internet of Things (IoT) platform in a particular year, the impact of this platform on the firm's production efficiency will not be confined to that year alone but will continue to influence subsequent years. Consequently, for each firm, the degree of digital transformation in any given year is considered as the aggregate value of all previous years' efforts and advancements. By applying all these steps mentioned before, a firm-year observation on the degree of digital transformation is obtained. The illustrated process of constructing the variable digital transformation is shown in Figure 11.

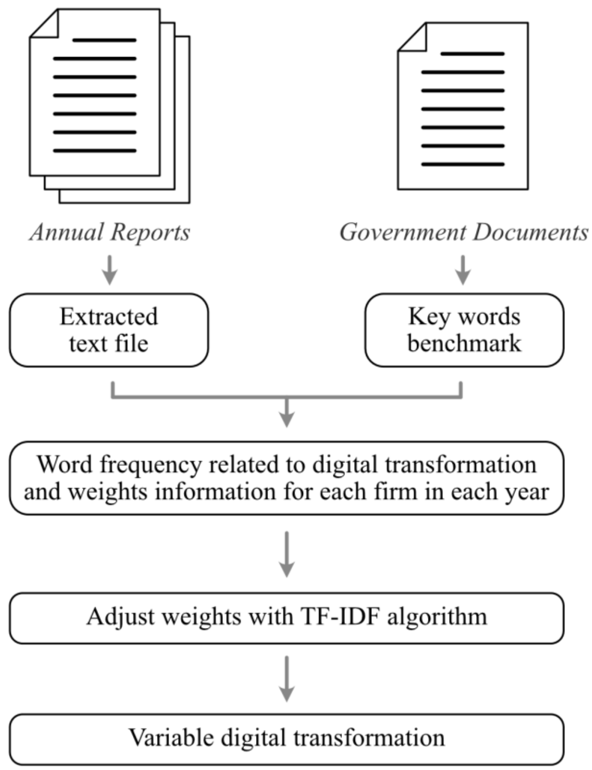


Figure 11. Construction of variable digital transformation

3.3.5. Control Variables

In this analysis, a set of control variables is included to account for various aspects of firm characteristics and financial structure, each defined and quantified as follows:

Firm Size and Leverage: The variable "$Size$" is quantified as the natural logarithm of total assets at the end of the year, providing a normalised measure of firm size that mitigates the influence of extreme values. The leverage ratio ("Lev") is defined as the ratio of total liabilities at year-end to total assets at year-end. This ratio measures the extent to which a company is financing its operations through debt rather than wholly owning its assets.

Profitability and Growth: Return on Assets ("ROA") is calculated as the ratio of net income to the average total assets for the year, offering a measure of how effectively a firm converts the money it has invested in assets into profits. The growth rate of a firm ("$Growth$") is measured by the year-on-year percentage increase in operating revenue, calculated as this year's operating revenue divided by the previous year's operating revenue, minus one. This metric assesses the firm's ability to increase its sales output over time.

Market Valuation and Governance: The book-to-market ratio ("BM") is defined as the ratio of book value to total market value, providing insight into valuation as perceived by the market relative to its recorded net assets. The price-to-book ratio ("PB") is calculated as the share price divided by per-share net assets, indicating how much investors pay for a dollar of net assets. The proportion of independent directors ("$Indep$") is calculated as the ratio of independent directors to the total number of directors, which can reflect the level of governance independence in firm decision-making.

Ownership and Firm Maturity: The shareholding proportion of the largest shareholder ("$Top1$") is measured by the number of shares held by the largest shareholder divided by the total number of shares, which can indicate the concentration of ownership and potential influence on management. The age of the firm ("$Firmage$") is calculated using the natural logarithm of the number of years since the firm was established, providing a scalar transformation that reflects firm maturity and potential lifecycle effects.

Liability Structure: The control variables also include total liabilities and current liabilities, both of which are absolute figures from the balance sheet. These measures provide insight into the firm's short-term and long-term financial obligations, which are crucial for understanding the firm's liquidity and financial health.

Each of these variables is chosen to provide a comprehensive understanding of the firm's operational context, financial health, and governance structure, facilitating a nuanced analysis of the primary variables of interest in the study.

3.3.6. Empirical Test Design

Given that this study is based on panel data, the primary regression model employs a high-dimensional fixed effects approach. Specifically, I control for time-fixed effects and firm-specific fixed effects. Additionally, to account for common characteristics within different industries, I use robust standard errors clustered at the industry level. The regression model for Hypothesis 1 is specified as follows:

$$ExportV_{it} = \beta_0 + \beta_1 Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

Where:

$ExportV_{it}$ is the core independent variable, referring to the total export value of the firm i

on year t.

$Digital_{it}$ is the core dependent variable, referring to the degree of digital transformation of the firm i on year t.

$Control$ are the predefined control variables of the regression.

α_i represents the firm fixed effects.

γ_t represents the firm fixed effects.

ϵ_{it} is the error term clustered by industry.

The regression models for Hypotheses 2 and 3 follows a similar setup. To conserve space, a detailed discussion of these models will be provided in the results section.

3.3.7. Descriptive Statistics and Correlation Analysis

The descriptive statistics and correlation analysis for the primary variables in this study are presented in Table 3 and Table 4, respectively. Table 3 reveals substantial differences in scale among the variables. Directly including these variables in the regression models could result in coefficients with inconsistent economic interpretations. To ensure that the estimated coefficients are meaningful and comparable, the core explanatory and dependent variables are normalised.

The correlation analysis in Table 4 indicates a significant positive correlation between digital transformation and export performance. However, the impact of digital transformation on capital efficiency and labour efficiency is less pronounced. This finding underscores the necessity for a more detailed examination of the internal mechanisms through which digital transformation affects export performance.

Table 3. Descriptive statistics

Variable	N	Mean	p50	SD	Min	Max
ExportV	9682	134.6	20.68	467.0	0.0	10198
CapitalE	9682	0.678	0.566	0.549	0.00200	10.59
LabourE	9664	15.52	9.549	64.13	0.0830	5496
Digital	9682	0.691	0.262	1.267	0.000	15.92
Size	9682	22.09	21.90	1.318	15.73	28.51
Lev	9682	0.463	0.436	0.812	0.00800	63.97
ROA	9682	0.0410	0.0360	0.290	-14.59	20.79
Growth	9682	0.727	0.110	22.30	-0.942	1878
Indep	9682	0.372	0.333	0.0560	0.182	0.800
BM	9682	0.930	0.604	1.040	0.00400	13.71
PB	9682	4.548	2.937	50.35	-2977	2789
Firmage	9682	2.729	2.773	0.379	0.693	3.912
Top1	9682	0.355	0.337	0.151	0.0220	0.900
Liabilities	9682	0.00900	0.00100	0.0470	0.0000	1.101
Current Liabilities	9682	0.00700	0.00100	0.0330	0.0000	0.800

Table 4. Correlation analysis

(obs=9,664)	*ExportV*	*CapitalE*	*LabourE*	*Digital*	*Size*	*Lev*	*ROA*	*Growth*	*Indep*	*BM*	*PB*	*Firmage*	*Top1*	*Liabilities*	*Current Liabilities*
ExportV	1.000														
CapitalE	0.129	1.000													
LabourE	0.014	0.196	1.000												
Digital	0.062	-0.026	-0.025	1.000											
Size	0.305	0.073	0.039	0.080	1.000										
Lev	0.033	0.051	0.060	-0.012	0.059	1.000									
ROA	-0.004	0.008	-0.026	0.002	-0.004	-0.472	1.000								
Growth	-0.005	0.006	0.011	-0.008	0.045	0.010	0.002	1.000							
Indep	0.006	-0.043	-0.015	0.034	0.052	0.003	0.001	-0.005	1.000						
BM	0.206	0.083	0.061	-0.049	0.628	0.130	-0.049	0.033	0.053	1.000					
PB	-0.011	0.010	-0.005	0.001	-0.058	0.003	0.142	0.000	0.010	-0.036	1.000				
Firmage	0.047	0.045	0.026	0.048	0.110	0.068	-0.013	0.016	-0.034	0.064	0.005	1.000			
Top1	0.071	0.100	0.027	-0.028	0.258	-0.009	0.019	0.014	0.052	0.161	-0.012	-0.127	1.000		
Liabilities	0.252	0.043	0.018	-0.001	0.496	0.051	-0.007	0.095	0.131	0.399	-0.011	-0.044	0.192	1.000	
Current Liabilities	0.274	0.058	0.022	0.003	0.502	0.054	-0.007	0.092	0.144	0.418	-0.011	-0.049	0.194	0.982	1.000

3.4. Results

3.4.1. Baseline Results

In this section, the empirical tests based on the prior analysis and developed hypotheses will be shown. Given the substantial scale variations among the variables involved in our regression, the key variables, export value and digital transformation are normalised prior to the analysis.

Table 5 presents the basic regression results, detailing the impact of digital transformation on export performance. Column 1 shows the results of a univariate regression, revealing a significant positive correlation between digital transformation and export value at the 0.01 level. The results from column 1 indicate that a one standard deviation increase in digital transformation corresponds to a 0.112 standard deviation increase in export value, equivalent to an annual increase of $52.30 million.

To address potential confounding variables, control variables such as $Size$, Leverage (Lev), Return on Assets (ROA), Growth, Independence ($Indep$), Book-to-Market ratio (BM), Price-to-Book ratio (PB), $Firmage$, $Top1$ (largest shareholder's ownership), $Liabilities$, and $Current\ Liabilities$ are introduced in column 2. The results from column 2 continue to show a significant positive impact of digital transformation on export value at the 0.01 level. Although the core regression coefficient decreased, a one standard deviation increases in digital transformation still resulted in a 0.0732 standard deviation increase in export value, equating to an annual increase of $34.18 million. Compared to column 1, the coefficient of Digital in column 2 is significantly reduced, and several control variables, including firm size, Growth, Independence, Firm age, Liabilities, and Current Liabilities, show significant impacts on export value. This indicates that the control variables successfully absorbed unobserved effects and served their intended purpose in the regression.

Table 5. Effect of digital transformation on export performance

	(1) *ExportV*	(2) *ExportV*	(3) *ExportV*	(4) *ExportV*
Digital	0.1119***	0.0732***	0.0661***	0.0661***
	(6.15)	(4.23)	(3.61)	(3.59)
Size		0.1684***	0.0260**	0.0260*
		(16.40)	(2.32)	(1.92)
Lev		0.0140	0.0046	0.0046**
		(1.02)	(0.75)	(2.54)
ROA		0.0070	0.0107	0.0107**
		(0.18)	(0.66)	(2.70)
Growth		-0.0013***	-0.0002	-0.0002
		(-2.95)	(-1.29)	(-1.16)
Indep		-0.6422***	-0.0830	-0.0830**
		(-3.70)	(-0.73)	(-2.20)
BM		-0.0089	-0.0107	-0.0107
		(-0.73)	(-1.31)	(-0.95)
PB		0.0001	-0.0001	-0.0001***
		(0.33)	(-0.67)	(-11.22)
Firmage		0.0752***	0.0979	0.0979
		(2.91)	(1.56)	(1.00)
Top1		-0.0699	-0.0691	-0.0691**
		(-1.06)	(-0.94)	(-2.57)
Liabilities		-10.1794***	-4.4388***	-4.4388***
		(-9.46)	(-5.30)	(-5.74)
Current Liabilities		19.7643***	8.1941***	8.1941***
		(12.62)	(6.94)	(3.01)
Constant	0.0306***	-3.6788***	-0.7715***	-0.7715
	(2.71)	(-15.92)	(-2.58)	(-1.65)
Control	No	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Time FE	No	No	Yes	Yes
Robust SE	No	No	No	Yes
Adjusted R^2	0.0039	0.1252	0.9102	0.9102
N	9682	9682	9682	9682

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Given the use of panel data, it was necessary to control for individual fixed effects and time fixed effects to eliminate firm-specific characteristics that do not change over time and time-specific characteristics that do not change across firms. The results, shown in column 3, indicate that the impact of digital transformation on export performance slightly decreases in magnitude compared to columns 1 and 2, but remains statistically significant at the 0.01 level. Furthermore, the influence of firm size on export value significantly diminishes both numerically and statistically, while the effects of Growth, Independence, and Firm age are no longer significant.

This confirms that the inclusion of fixed effects effectively captured the potential firm-specific and time-specific factors.

Column 4 represents the most stringent regression specification. Although financial firms were excluded during sample selection, significant industry differences persisted among the remaining firms. To control for these differences, column 4 employs industry-clustered robust standard errors based on the foundation of column 3. The results from column 4 demonstrate that the impact of digital transformation on export performance remains significant. A one standard deviation increase in digital transformation leads to a 0.0661 standard deviation increase in export value, amounting to an annual increase of $30.87 million. Additionally, control variables such as Size, Leverage, and Price-to-Book ratio (PB) continue to significantly affect export performance.

Overall, the results from columns 1 through 4 consistently show that digital transformation has a significant and robust positive impact on export value across various empirical designs, thereby validating Hypothesis 1, which means digital transformation can enhance firms' export performance.

3.4.2. Mediating Effect of Capital Efficiency and Labour Efficiency

Based on the empirical test of Hypothesis 1, I further investigated the internal mechanisms through which digital transformation enhances firms' export performance. As analysed in Chapter 2 and the hypothesis development section, digital transformation can increase both capital efficiency and labour efficiency from an input-output perspective. In the digital age, these improvements in efficiency align with the two core dimensions required for firms to maintain their Firm-Specific Advantages (FSAs): technology advantage and human capital advantage.

In Table 6, I tested the mediating effects of capital efficiency and labour efficiency using the stepwise regression approach proposed by Baron and Kenny (Baron & Kenny, 1986). Specifically, the first column confirms the significant impact of digital transformation on export performance, consistent with the empirical design of Model 4 in Table 5. Next, columns 2 and 3 validate the impact of digital transformation on the two mediating variables, capital efficiency and labour efficiency, respectively. Subsequently, column 4 examines the influence of these mediating variables on export performance. Finally, column 5 presents the results when digital transformation and the two mediating variables are included together in the regression model.

The results from columns 2 and 3 indicate that digital transformation has a significant positive impact on both capital efficiency and labour efficiency. Column 4 shows that while capital efficiency has a positive effect on export performance, labour efficiency does not significantly enhance export performance. In column 5, the positive effect of digital transformation on export performance slightly weakens after including the mediating variables, with capital efficiency showing a significant positive path to export performance, whereas the path for labour efficiency remains insignificant.

From the analysis of Table 6, it can be concluded that, on average, the improvement in capital efficiency is one of the internal mechanisms through which digital transformation enhances export performance. However, there is no clear evidence supporting the notion that digital transformation improves export performance through increased labour efficiency. This result suggests that, in maintaining FSAs, meeting the technology dimension of advantage is generally more critical. Thus, the findings support Hypothesis H2a but not Hypothesis H2b.

Table 6. Mediation effect of capital efficiency and labour efficiency

	(1) *ExportV*	(2) *CapitalE*	(3) *LabourE*	(4) *ExportV*	(5) *ExportV*
Digital	0.0661***	0.0681***	0.0974***		0.0646***
	(3.59)	(4.76)	(3.45)		(3.60)
CapitalE				0.0212***	0.0199***
				(3.20)	(3.09)
LabourE				0.0006	0.0005
				(0.62)	(0.48)
Size	0.0260*	-0.1608***	-0.1988*	0.0348**	0.0295*
	(1.92)	(-6.49)	(-1.87)	(2.19)	(1.93)
Lev	0.0046**	-0.0245	0.0560***	0.0049**	0.0043**
	(2.54)	(-1.59)	(3.55)	(2.64)	(2.33)
ROA	0.0107**	-0.0386	-0.0578***	0.0150**	0.0137**
	(2.70)	(-0.69)	(-2.97)	(2.43)	(2.26)
Growth	-0.0002	0.0010	0.0007***	-0.0002	-0.0002
	(-1.16)	(1.34)	(3.08)	(-1.20)	(-1.21)
Indep	-0.0830**	0.0708	-0.1469**	-0.0844**	-0.0817**
	(-2.20)	(0.62)	(-2.31)	(-2.20)	(-2.12)
BM	-0.0107	-0.0297**	0.0638**	-0.0114	-0.0103
	(-0.95)	(-2.71)	(2.81)	(-0.96)	(-0.91)
PB	-0.0001***	0.0002***	-0.0001***	-0.0001***	-0.0001***
	(-11.22)	(6.42)	(-3.15)	(-9.88)	(-9.66)
Firmage	0.0979	0.3038**	0.2730	0.1058	0.0914
	(1.00)	(2.66)	(1.59)	(1.10)	(0.96)
Top1	-0.0691**	-0.1693**	-0.0350	-0.0782**	-0.0705**
	(-2.57)	(-2.76)	(-0.49)	(-2.68)	(-2.58)
Liabilities	-4.4388***	-1.3768	-1.4060	-4.4802***	-4.4100***
	(-5.74)	(-1.24)	(-1.00)	(-5.64)	(-5.54)
Current Liabilities	8.1941***	2.1395	3.2607	8.1884***	8.1479***
	(3.01)	(1.35)	(1.31)	(3.00)	(2.98)
Constant	-0.7715	2.9234***	3.6820*	-1.0035*	-0.8323
	(-1.65)	(6.61)	(1.97)	(-1.93)	(-1.67)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.9102	0.8680	0.2823	0.9101	0.9102
N	9682	9682	9682	9682	9682

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The analysis in Table 6 provides preliminary evidence that capital efficiency is one of the mechanisms through which digital transformation enhances export performance. However, the impact of digital transformation on labour efficiency remains uncertain. As discussed in Chapter 2, the general equilibrium model suggests that there is significant heterogeneity in the baseline levels of capital efficiency and labour efficiency across firms, which directly influences the marginal effects of digital transformation on these efficiencies. Furthermore, according to the theory of limited resources, implementing digital transformation entails costs, and firms cannot allocate unlimited resources to simultaneously enhance both capital efficiency and labour efficiency. Therefore, firms must carefully allocate resources during the digital transformation process. As mentioned in Chapter 2, given certain levels of investment in digital transformation, firms face an optimal allocation between improving capital efficiency and labour efficiency.

3.4.3. Heterogeneity Analysis

In the model, differences among firms are primarily reflected in their levels of capital efficiency and labour efficiency. Therefore, this section focuses on firm heterogeneity to address two key issues. First, this section explores the underlying reasons for the insignificant mediating effect of labour efficiency. This is done by grouping firms based on their levels of capital and labour efficiency and then examining the contribution of each efficiency to export performance. Second, this section investigates the optimal investment strategy for digital transformation across different types of firms.

Specifically, to capture the interaction between labour efficiency and capital efficiency, an interaction variable is constructed. Next, the firms are classified into four groups based on the median levels of capital efficiency and labour efficiency: high capital efficiency-high labour efficiency (High-High), high capital efficiency-low labour efficiency (High-Low), low capital efficiency-high labour efficiency (Low-High), and low capital efficiency-low labour efficiency (Low-Low). Then the regression analyses are conducted on both the full sample and the four subgroups. The results are presented in Table 7.

Table 7. Efficiencies and interaction by 2*2 group

ExportV	(1) ALL	(2) High-High	(3) High-Low	(4) Low-High	(5) Low-Low
Digital	0.0646***	0.1557***	0.1243	-0.0910***	0.0226
	(3.58)	(4.88)	(1.37)	(-4.94)	(1.71)
CapitalE	0.0246***	0.0300***	0.1127	0.0586**	0.0687*
	(3.95)	(3.52)	(0.29)	(2.96)	(1.92)
LabourE	0.0034**	0.0022	0.6532*	-0.0103	0.8347***
	(2.54)	(0.34)	(1.92)	(-0.73)	(4.31)
Interaction	-0.0040**	-0.0053*	-0.1015	-0.0259	0.4253*
	(-2.57)	(-2.16)	(-0.04)	(-0.60)	(1.82)
Size	0.0302*	0.0444	0.0115	0.0433**	-0.0395**
	(2.04)	(1.09)	(0.34)	(2.49)	(-2.44)
Lev	0.0042**	0.1610	0.0116	0.0124	-0.0011
	(2.29)	(1.23)	(0.35)	(0.42)	(-0.32)
ROA	0.0139**	0.0930**	-0.0146	0.1274	-0.0060
	(2.24)	(2.56)	(-0.48)	(1.31)	(-1.03)
Growth	-0.0002	-0.0003***	0.0103	0.0001	-0.0029
	(-1.23)	(-13.40)	(1.63)	(1.14)	(-1.71)
Indep	-0.0832*	-0.7712***	0.6057***	-0.1001	0.1499
	(-2.05)	(-6.91)	(4.31)	(-0.52)	(1.40)
BM	-0.0094	0.0021	0.0917	-0.0000	-0.0261
	(-0.82)	(0.11)	(0.72)	(-0.00)	(-0.72)
PB	-0.0001***	-0.0006***	0.0000**	0.0001	0.0000*
	(-9.64)	(-10.53)	(2.79)	(0.82)	(1.91)
Firmage	0.0909	-0.1613	0.1172	-0.0351	0.0468
	(0.96)	(-0.52)	(1.20)	(-0.65)	(0.26)
Top1	-0.0710**	-0.0980	-0.4545**	-0.0108	0.1689**
	(-2.56)	(-0.62)	(-2.95)	(-0.17)	(2.26)
Liabilities	-4.4180***	-3.5920***	-10.3909	-7.5428**	6.2663
	(-5.56)	(-3.84)	(-0.40)	(-2.26)	(0.71)
Current Liabilities	8.1561***	8.7222*	3.5162	9.8719**	11.4144**
	(2.99)	(2.06)	(0.13)	(2.30)	(2.64)
Constant	-0.8476*	-0.1557	-0.5222	-0.9216***	0.5919*
	(-1.75)	(-0.10)	(-0.49)	(-3.57)	(1.84)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.9102	0.9296	0.9291	0.9525	0.8854
N	9682	2891	1560	1514	2803

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 presents the regression results for the full sample (Column 1) and for four subgroups classified by capital efficiency and labour efficiency levels: High-High, High-Low, Low-High, and Low-Low (Columns 2 to 5). The analysis aims to investigate two core issues: the insignificant mediating effect of labour efficiency and the optimal investment strategy for digital transformation across different firms. For clarity, the coefficients of key variables are visualised by plotting capital efficiency on the x-axis and labour efficiency on the y-axis. The coordinate plane is divided into four regions, each corresponding to one of the four regression groups. The detailed graph is shown in Figure 12.

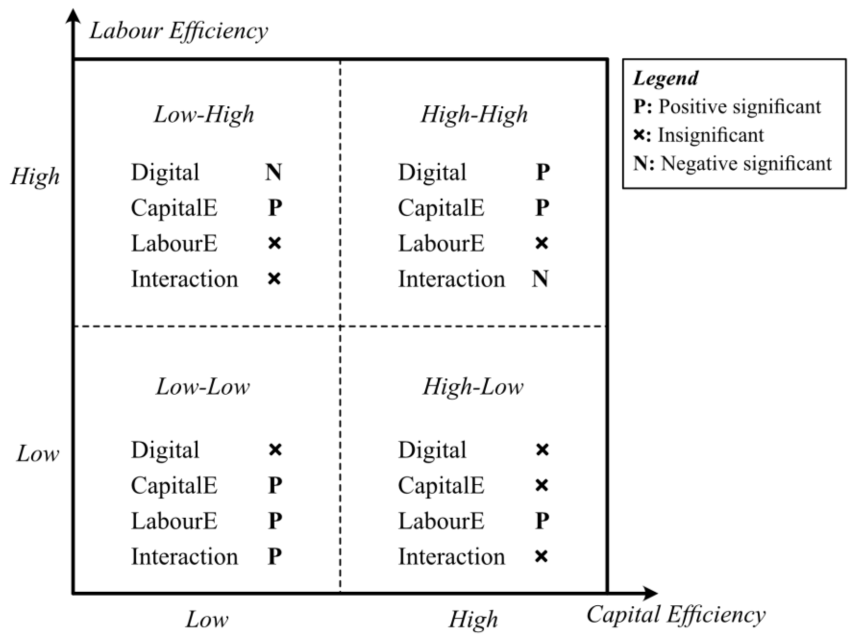


Figure 12. The effects of variables on export performances

Figure 12 illustrates four distinct groups, each representing different combinations of high and low capital and labour efficiency. Within each group, four core variables of interest are displayed along with their significance indicators. Specifically, 'P' indicates that the variable has a significantly positive effect on firms' export value ($ExportV$), 'N' indicates a significantly negative effect, while 'x' denotes that the variable has no statistically significant impact on firms' export value.

In the High-High group, digital transformation significantly impacts export performance at the 0.01 level. Capital efficiency shows a significant positive impact on export performance, while labour efficiency does not. Additionally, the interaction term between capital efficiency and labour efficiency is significantly negative. This suggests that for firms with high levels of both efficiencies, digital transformation further optimizes capital efficiency, thereby enhancing export performance. However, additional investment in labour efficiency does not improve export performance and may even inhibit the positive effects of capital efficiency. Similar analyses apply to the other groups: (a) in the High-Low group, digital transformation enhances export performance primarily through labour efficiency; (b) in the Low-High group, it does so mainly through capital efficiency; (c) in the Low-Low group, digital transformation improves export performance through both efficiencies, with a mutually reinforcing effect.

These empirical results yield two key outcomes. First, they address the heterogeneity in the effects of the two mechanisms. Table 6 shows no evidence that labour efficiency is a mediating mechanism for digital transformation's impact on export performance in the full sample. This could be due to two possible reasons:

If the labour efficiency mechanism genuinely does not exist, this non-significance should be consistent across all subgroups in Table 7. This would imply a discrepancy between empirical evidence and theoretical analysis, suggesting that while digital transformation enhances labour efficiency, higher labour efficiency does not contribute to export performance, offering only technological advantages without satisfying the requirement for human capital advantages.

Alternatively, the labour efficiency mechanism may exist under specific conditions, with heterogeneity across firms causing the average treatment effect in the full sample to be offset.

The subgroup analysis supports the second possibility. Comparing the full sample results with the subgroup regressions shows that digital transformation indeed enhances export performance through both capital efficiency and labour efficiency, with capital efficiency being the dominant mechanism overall. However, the effectiveness of each efficiency is limited to specific contexts.

Second, this empirical result addresses the theoretical optimal transformation strategy derived from Chapter 2's general equilibrium model. While digital transformation can enhance efficiency, the theory proves that unlimited investment in digital transformation is not always optimal for firms. Firms must balance the costs and benefits of digital transformation, allocating resources to achieve optimal efficiency improvements.

In the High-High group, firms already have high levels of both capital and labour efficiency, leaving little room for human capital optimization. Therefore, improving export performance relies mainly on enhancing capital efficiency. The significant negative interaction term supports the theory of diminishing marginal returns in the CES production function framework, where additional investments in either efficiency reduce the marginal benefits of the other.

For the High-Low and Low-High groups, the results indicate that when a firm's efficiencies deviate from the optimal ratio, focusing on improving the relatively lower efficiency significantly boosts export performance. For instance, in the High-Low group, improving labour efficiency markedly enhances export performance, while improving capital efficiency does not have a significant effect.

In the Low-Low group, both efficiencies are at low levels, so enhancing either capital or labour efficiency significantly improves export performance. The positive interaction term suggests that simultaneously improving both efficiencies offers additional benefits. This result aligns with the theoretical model in Chapter 2, supporting the existence of an optimal digital transformation efficiency allocation strategy for firms.

3.4.4. Discussions on the Empirical Result

While the empirical findings above consistently demonstrate the positive impact of digital transformation on firms' export performance, an intriguing and somewhat counterintuitive result emerges for firms characterized by low initial labour efficiency. Specifically, our results suggest that for these firms, excessive digital transformation does not necessarily translate into higher export performance and can even exert a negative effect. Although this result appears to contradict the general positive effect of digital transformation, it can be clearly understood through a nuanced consideration of the associated costs, capabilities, and internal adjustment processes.

First, digital transformation inherently involves significant upfront investment costs and ongoing management expenses, including purchasing and integrating advanced digital equipment, licensing sophisticated software platforms, and substantial expenditure on employee training. Particularly, the digitalisation of operational processes requires not only financial investments but also considerable time for learning and adaptation. For firms initially exhibiting low labour efficiency, employees typically lack the advanced skill sets, experience, or adaptive capacities required to quickly assimilate and effectively utilize these new digital technologies. Therefore, when digital transformation surpasses a certain threshold, the incremental benefits derived from improved operational efficiency may diminish quickly due to limited employee absorptive capacity, resulting in marginal returns that no longer justify the substantial investments.

Second, beyond purely financial considerations, over-investment in digital transformation in a context of low labour efficiency may create internal organisational friction or resistance. Employees facing digital tools or processes that exceed their current skills can experience heightened workloads, stress, or demoralisation. Rather than facilitating smooth operational improvements, such poorly matched digital initiatives may disrupt existing workflows, thereby harming productivity in the short and medium term. Consequently, such inefficiencies not only offset expected productivity gains but may also negatively affect product quality, customer satisfaction, and ultimately, export competitiveness.

Third, these findings align with the theoretical insights established in Chapter 2's general equilibrium model, which explicitly consider the interplay between capital and labour efficiency under digital transformation. The theoretical analysis underscores that optimal investment strategies depend crucially on firms' initial factor endowments, suggesting an optimal balance rather than unilateral or overly aggressive digital transformation strategies. Firms with low initial labour efficiency must therefore prioritise targeted investments that progressively enhance employee capabilities and adaptability—such as incremental training programs and phased technology upgrades—rather than pursuing rapid, comprehensive digital transformations.

In summary, while digital transformation broadly benefits firm export performance, our empirical analysis highlights critical boundary conditions: firms with low labour efficiency must carefully calibrate their digitalisation efforts, aligning investment levels closely with their internal absorptive capacity and labour skill development trajectory. Failure to do so risks incurring disproportionately high costs with minimal productivity gains, thereby negatively affecting overall export performance.

3.5. Robustness Tests

This study aims to be as comprehensive as possible in terms of theoretical construction, empirical design, variable selection, and data collection. To minimise potential biases and ensure the accuracy of our analysis, this section conducts four types of robustness tests. First, on the epistemological level, this section provides an alternative perspective on whether export value or export volume better represents firm export performance and conducted empirical tests based on this perspective. Second, this section introduces an alternative measure of digital transformation to test the accuracy of the regression results. Third, on the methodological level, this section proposes the Generalized Method of Moments (GMM) as an alternative approach to the high-dimensional fixed effects model used in the empirical design. Fourth, in terms of causal inference, this section employs a two-dimensional instrumental variable approach to address endogeneity issues.

3.5.1. Alternative Measurement of Export Performance

In the main regression stage, this study uses the total trade value (in USD) of a firm's products across different trade methods as a proxy for export performance. However, using the total trade volume of a firm's products across different trade methods as a proxy also has unique advantages. First, trade volume directly reflects the actual quantity of products a firm export to international markets, avoiding the instability of trade value caused by price and exchange rate fluctuations, thus providing a stable and reliable measure. Second, using trade volume as an alternative measure can validate the robustness of the research results, ensuring that the conclusions do not depend on a single export performance indicator and increasing the credibility and broad applicability of the findings. Therefore, this section employs the total trade volume of a firm's products across different trade methods as the proxy for export performance, conducting baseline regressions and mediation effect tests. The regression results are presented in Table 8.

In Table 8, the dependent variable is the total export volume of a firm's products, denoted as $ExportQ$. Columns 1 and 2 present the baseline results. The regression results indicate that digital transformation has a significantly positive impact on export volume at the 0.01 level, consistent with the main regression results, thereby confirming the robustness of the baseline regression. Column 3 presents the mediation effect test results, showing that capital efficiency has a robust mediating effect, while labour efficiency does not. This finding supports the earlier analysis, suggesting that capital efficiency plays a dominant role in the two mechanisms, whereas the mediating role of labour efficiency is not stable. Overall, using export volume as the dependent variable validates the robustness of this study's findings.

Table 8. Alternative measurement of export performance

	(1)	(2)	(3)
	ExportQ	*ExportQ*	*ExportQ*
Digital	0.1393***	0.1393***	0.1361***
	(8.71)	(3.17)	(3.23)
CapitalE			0.0214***
			(5.22)
LabourE			0.0003
			(0.30)
Interaction			0.0004
			(0.29)
Size	0.0573***	0.0573***	0.0613***
	(5.85)	(7.27)	(6.36)
Lev	0.0108**	0.0108**	0.0091*
	(2.02)	(2.16)	(1.97)
ROA	0.0246*	0.0246**	0.0312**
	(1.74)	(2.37)	(2.59)
Growth	0.0001	0.0001	0.0001
	(0.55)	(1.01)	(0.62)
Indep	0.0246	0.0246	0.0151
	(0.25)	(0.24)	(0.15)
BM	0.0047	0.0047	0.0057
	(0.66)	(0.83)	(1.00)
PB	-0.0001	-0.0001***	-0.0001***
	(-1.56)	(-4.14)	(-4.16)
Firmage	0.2646***	0.2646***	0.2523***
	(4.82)	(8.93)	(9.11)
Top1	-0.0202	-0.0202	-0.0271
	(-0.31)	(-0.42)	(-0.54)
Liabilities	-0.9191	-0.9191*	-0.8909*
	(-1.26)	(-1.94)	(-1.84)
Current Liabilities	-0.5874	-0.5874	-0.6342
	(-0.57)	(-0.49)	(-0.53)
Constant	-1.9153***	-1.9153***	-1.9694***
	(-7.34)	(-10.86)	(-9.75)
Control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Robust SE	No	Yes	Yes
Adjusted R^2	0.9289	0.9289	0.9291
N	9526	9526	9508

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.2. Alternative measurement of digital transformation

In the baseline regression analysis of this study, the fact that the effects of digital transformation extend beyond the current period and persist into subsequent years is accounted for. Therefore, the cumulative value of digital transformation from the observation year and prior years is used as the indicator for the firm's digital transformation in the given year. However, digital equipment and services may deteriorate or become poorly maintained over time, potentially diminishing the long-term efficiency gains from digital transformation. To address this concern, an incremental measure of digital transformation is used as an alternative metric.

Given that digital equipment and services require some time for installation, adjustment, and employee adaptation, this alternative measurement lags the incremental digital transformation measure by one period, denoted as $digital\_alt$. After conducting baseline regression and mediating effect tests using this alternative measure, the results are presented in Table 9.

Column 1 of Table 9 shows the impact of digital transformation on export performance. Columns 2 and 3 display the effects of digital transformation on capital efficiency and labour efficiency, respectively. Column 4 presents the mediation effect. The regression results are consistent with the previous section's analysis, confirming the robustness of the baseline regression results and the theoretical analysis.

Table 9. Alternative measurement of digital transformation

	(1) ExportV	(2) CapitalE	(3) LabourE	(4) ExportV
Digital_alt	0.0085***	0.0113**	0.0001	0.0082***
	(4.00)	(2.53)	(0.07)	(3.74)
CapitalE				0.0262**
				(2.63)
LabourE				-0.0047*
				(-1.87)
Interaction				-0.0045
				(-1.51)
Size	0.0170	-0.1874***	0.1286**	0.0239
	(0.77)	(-3.77)	(2.37)	(1.02)
Lev	0.0056	-0.0236	0.0093	0.0049
	(0.62)	(-1.20)	(1.33)	(0.59)
ROA	0.0210	-0.0800	0.0443	0.0188
	(0.54)	(-0.95)	(1.07)	(0.52)
Growth	-0.0001	0.0009	0.0002*	-0.0002
	(-0.62)	(1.25)	(1.94)	(-0.72)
Indep	-0.1703**	0.0571	-0.0515	-0.1725**
	(-2.54)	(0.57)	(-0.65)	(-2.43)
BM	-0.0125	-0.0188	-0.0074	-0.0115
	(-0.60)	(-0.99)	(-0.30)	(-0.55)
PB	-0.0000***	-0.0000	-0.0000	-0.0000***
	(-7.34)	(-0.97)	(-0.80)	(-8.73)
Firmage	0.3012**	0.4605**	0.0166	0.2912**
	(2.29)	(2.80)	(0.40)	(2.29)
Top1	-0.1407***	-0.2723***	0.0319	-0.1366***
	(-3.79)	(-3.04)	(0.52)	(-3.62)
Liabilities	-5.7483***	-1.6653	-1.1957	-5.7378***
	(-7.33)	(-1.25)	(-1.02)	(-7.25)
Current Liabilities	9.5807***	3.1787*	1.4507	9.5396***
	(4.22)	(1.94)	(0.87)	(4.21)
Constant	-1.0666	3.0969***	-2.8808**	-1.1964
	(-1.44)	(3.53)	(-2.38)	(-1.59)
Control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.9158	0.8779	0.7055	0.9159
N	7098	7098	7090	7090

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.3. Robustness Check Using GMM Estimation

In the baseline regression, this study employs a high-dimensional fixed effects model. While this model effectively addresses fixed effects and provides robust standard errors, the Generalized Method of Moments (GMM) estimation method offers unique advantages (Wooldridge, 2001). Firstly, GMM corrects for biases caused by endogeneity by using instrumental variables, thereby enhancing the reliability of the estimates. Secondly, compared to traditional fixed effects models, GMM can provide more efficient estimates under complex error structures. Thus, adopting the GMM method can validate the robustness of the high-dimensional fixed effects model results, ensuring the consistency and reliability of the research conclusions across different estimation methods.

In our GMM estimation framework, the primary explanatory variable—digital transformation—is treated as potentially endogenous. To adequately handle this endogeneity, we follow established econometric practices by using the lagged values of digital transformation as internal instruments. Specifically, we employ the second and third lags of digital transformation in estimations related to export performance and capital efficiency, and only the second lag in estimations related to labour efficiency. This approach effectively utilizes past information of digital transformation to mitigate contemporaneous endogeneity issues.

To avoid instrument proliferation, which could weaken the reliability of the estimates, we employ a common practice in the literature by collapsing the set of instruments. This technique aggregates multiple lagged observations into fewer instrumental variables, thereby enhancing the efficiency and stability of the estimation results.

Additionally, all other control variables included in the model—such as firm size, leverage, profitability (ROA), growth opportunities, corporate governance indicators, valuation metrics (book-to-market and price-to-book ratios), firm age, ownership structure (top shareholder concentration), and liabilities—are considered exogenous or predetermined. These variables are thus directly included as standard instrumental variables, under the reasonable assumption that their current values are not directly influenced by firms' contemporaneous digital transformation decisions.

We implement the GMM estimation using the two-step robust estimator to correct for potential heteroscedasticity and autocorrelation issues within the panel data. Moreover, consistent with recommendations in prior empirical research, our estimation excludes the level equations and focuses exclusively on differenced equations to ensure model specification validity.

The results of the GMM estimation are presented in Table 10. Column 1 of Table 10 shows the impact of digital transformation on export performance. Columns 2 and 3 display the effects of digital transformation on capital efficiency and labour efficiency, respectively. The results across all three columns are consistent with those of the main regression, demonstrating the robustness of the empirical analysis in this study.

To verify the validity and reliability of our GMM estimation, we performed diagnostic tests including the Arellano–Bond tests for serial correlation and the Hansen test of overidentifying restrictions (Arellano & Bond, 1991; Hansen, 1982; Sargan, 1958). Specifically, the Arellano–Bond AR(1) and AR(2) tests yielded no significant evidence of first-order ($p = 0.334$) or second-order ($p = 0.392$) serial correlation in the differenced residuals, supporting the assumptions underlying our GMM specification. Moreover, both the Hansen test ($p = 0.106$) and the Sargan test ($p = 0.190$) indicate no significant problems regarding instrument validity, suggesting that our chosen instruments—specifically, the lagged values of digital transformation—are statistically appropriate. Although these results are reassuring and align with standard econometric practices, it should be noted that the limited degrees of freedom associated with the instrument set (only one degree of freedom) could potentially limit the power of the overidentification tests. Therefore, while the diagnostic tests generally confirm the robustness of our estimation results, cautious interpretation remains advisable.

Table 10. GMM estimation results

	(1) ExportV	(2) CapitalE	(3) LabourE
Digital	0.163***	0.322***	0.548**
	(0.048)	(0.080)	(0.231)
Size	0.010	-0.259***	0.723***
	(0.018)	(0.049)	(0.209)
Lev	0.024***	0.025	0.123
	(0.003)	(0.025)	(0.234)
ROA	0.051***	0.050	0.587
	(0.009)	(0.043)	(0.924)
Growth	-0.000	0.001**	0.003***
	(0.000)	(0.000)	(0.001)
Indep	-0.125	-0.072	0.079
	(0.130)	(0.145)	(0.653)
BM	0.025***	0.009	0.122**
	(0.008)	(0.010)	(0.058)
PB	-0.000	-0.000*	-0.001
	(0.000)	(0.000)	(0.001)
Firmage	0.104	-0.252**	-3.866***
	(0.078)	(0.109)	(0.749)
Top1	0.325***	0.434**	1.510
	(0.118)	(0.179)	(1.195)
Liabilities	0.214	-2.512*	-9.034
	(0.810)	(1.507)	(6.885)
Current Liabilities	-1.098	4.415**	12.118
	(1.251)	(1.891)	(9.562)
Robust	Yes	Yes	Yes
Twostep	Yes	Yes	Yes
Noleveleq	Yes	Yes	Yes
N	7237	7237	7237

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.4. Instrument Variables

The core explanatory variable of this study is the degree of digital transformation derived from textual analysis of corporate annual reports. However, this indicator may face endogeneity issues. Specifically, higher levels of economic development and more advanced international trade sectors in a firm's region can lead to better digital infrastructure and services, thereby facilitating digital transformation. This could result in reverse causality, potentially biasing the estimates. To address this issue, it is necessary to construct an instrumental variable.

Given that the empirical analysis is based on panel data, where the core explanatory variable, digital transformation, varies across both firm and time dimensions, traditional single-dimension instrumental variables based on geographic or temporal characteristics are not suitable. Therefore, following the approach of Nunn and Qian, this study constructs a two-dimensional instrumental variable (Nunn & Qian, 2014).

In the spatial dimension, historically, transportation hubs have been pivotal for information exchange and communication. These hubs also tend to have more developed supply chains and industrial organizations, leading to higher levels of economic development. In the digital economy era, new technologies, ideas, services, and platforms related to digital transformation are more prevalent in transportation hub areas. Thus, the accessibility of a firm's headquarters to transportation hubs is strongly associated with its exposure to digital technologies and platforms. If management and employees at the headquarters can easily access the latest information, services and platforms for digital transformation, the firm is more likely to achieve a higher degree of digital transformation, fulfilling the requirement for a strong correlation between the instrumental variable and the core explanatory variable. Moreover, the location of a firm's headquarters is relatively fixed and cannot be dynamically adjusted based on annual export performance. Even if the headquarters' location inherently provides better export conditions, this effect is entirely absorbed by individual fixed effects due to the immobility of office locations. Finally, observations where the headquarters and main factory locations coincide are excluded from the instrumental variable test. Based on these considerations, the location of a firm's headquarters satisfies the assumption of strong exogeneity concerning export performance.

To implement this approach, this part first obtained the addresses of corporate headquarters and main factories from annual reports, determined the latitude and longitude coordinates for each headquarters, and excluded observations where the headquarters and factory addresses were identical. Second, this study utilises the "National Transportation Hub Layout and Construction Plan" published by the Chinese government to identify 353 transportation hubs, including seaport, land port, and airport hubs, and calculated their latitude and longitude coordinates. Third, to measure the accessibility of these hubs for corporate management and employees, this method uses a path planning API provided by mapping services, combined with Python scripts, to calculate the commuting distance and time from each headquarters to these transportation hubs. Given the difficulty for management and employees to reach distant hubs, the three nearest transportation hubs are selected for each firm based on commuting distance and averaged these distances. Similarly, the commuting times to the three nearest hubs are averaged as well for each firm.

Unlike previous literature that calculates straight-line distances between two geographic coordinates, this method accounts for terrain and the convenience of the transportation network, significantly reducing bias. For commuting time, considering the core metric we are expected to obtain is the accessibility of new digital information and technologies for management and employees, the commuting distance may not be precise enough. Even with the same commuting distance, road conditions and speed limits can affect the effort required to reach the destination. Hence, commuting time better reflects the effort needed.

When calculating commuting time and distance, considering the different road permissions and speed limits for freight and passenger vehicles, this method includes only passenger vehicle routes in the API requests to avoid bias from freight vehicle data. Additionally, to avoid bias from varying traffic conditions on different days of the week or times of day, the departure time is standardised to 9:00 AM on Mondays. Based on these settings, the spatial component of the instrumental variable is obtained, namely the commuting distance and time for passenger vehicles from corporate offices to transportation hubs on weekday mornings, denoted as $travel\_distance$ and $travel\_time$.

In the temporal dimension, the level of digital economic development in a firm's location reflects the overall trend of digitalization over time and is strongly correlated with the firm's degree of digital transformation. Provincial software industry income serves as an ideal proxy for local digital economic development. As a macro-level indicator, provincial software income is largely unaffected by individual firms' export performance, thus ensuring exogeneity between a firm's export performance and the province's software industry income. Based on this premise, the temporal component of the instrumental variable is derived: the software industry income of the province where the firm is located, denoted as $software\_income$.

Combining the spatial and temporal indicators, a refined instrumental variable for digital transformation is constructed. Given the negative association between the spatial component and the degree of digital transformation, where shorter commuting times and distances are more likely to correspond with higher levels of digital transformation, these measures are inverted. The specific formulas for constructing the instrumental variables are as follows:

$$IV\_distance = \frac{1}{travel\_distance} \cdot soft\_income$$

$$IV\_time = \frac{1}{travel\_time} \cdot soft\_income$$

Using these constructions, $IV\_distance$ and IV_time serve as instrumental variables for the degree of digital transformation. Then the replication of the core baseline regression using these instruments are conducted. Both instrumental variables passed the weak instrument test, and the second-stage regression results are presented in Table 11 and Table 12. In which columns in Table 11 show the results using $IV\_distance$, while columns in Table 12 show the results using IV_time.

Table 11. IV Estimation: Commuting Distance as IV

	(1) *ExportV*	(2) *CapitalE*	(3) *LabourE*
Digital	3.8983***	0.9512**	1.0151**
	(4.19)	(2.02)	(2.33)
Size	-0.0613	-0.0248	-0.0167
	(-0.92)	(-0.74)	(-0.54)
Lev	-0.0271	0.0572**	0.0149
	(-0.57)	(2.37)	(0.66)
ROA	-0.0014	0.1043**	0.0035
	(-0.02)	(2.32)	(0.08)
Growth	-0.0007	0.0005	0.0004
	(-0.75)	(1.11)	(0.89)
Indep	-1.5439***	-0.9441***	-0.7424***
	(-3.10)	(-3.75)	(-3.19)
BM	0.1192***	0.0458**	0.0626***
	(2.62)	(1.99)	(2.94)
PB	-0.0001	0.0002	0.0001
	(-0.24)	(0.91)	(0.42)
Firmage	0.2023***	0.2733***	0.1040***
	(3.17)	(8.45)	(3.45)
Top1	0.3078*	0.7542***	0.4938***
	(1.71)	(8.31)	(5.86)
Liabilities	-7.3294***	-5.0158***	-2.3057*
	(-2.64)	(-3.57)	(-1.77)
Current Liabilities	17.9449***	8.7336***	4.0172**
	(4.60)	(4.43)	(2.20)
First-stage: IV_distance	0.1077***	0.1077***	0.1083***
	(4.52)	(4.52)	(4.54)
First-stage F-statistic	20.43	20.43	20.64
Stock-Yogo 10% Critical Value	16.38	16.38	16.38
Anderson canonical LM statistic	20.47	20.47	20.67
Anderson LM p-value	0.0000	0.0000	0.0000
Cragg-Donald Wald F-statistic	20.43	20.43	20.64
Anderson-Rubin Wald Chi-sq	90.41	5.1	7.6
Anderson-Rubin Wald p-value	0.0000	0.0239	0.0059
Stock-Wright LM S statistic	89.9	5.12	7.62
Stock-Wright LM p-value	0.0000	0.0237	0.0058
Control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	9546	9546	9537

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12. IV Estimation: Commuting Time as IV

	(1) *ExportV*	(2) *CapitalE*	(3) *LabourE*
Digital	3.7715***	1.0222**	0.8732**
	(4.70)	(2.41)	(2.35)
Size	-0.0529	-0.0295	-0.0073
	(-0.91)	(-0.96)	(-0.27)
Lev	-0.0253	0.0562**	0.0169
	(-0.55)	(2.31)	(0.79)
ROA	-0.0014	0.1043**	0.0035
	(-0.02)	(2.28)	(0.09)
Growth	-0.0007	0.0006	0.0004
	(-0.79)	(1.11)	(0.89)
Indep	-1.5026***	-0.9673***	-0.6962***
	(-3.24)	(-3.95)	(-3.23)
BM	0.1145***	0.0484**	0.0574***
	(2.76)	(2.21)	(2.98)
PB	-0.0001	0.0002	0.0001
	(-0.23)	(0.88)	(0.47)
Firmage	0.2000***	0.2746***	0.1013***
	(3.24)	(8.43)	(3.52)
Top1	0.2947*	0.7616***	0.4790***
	(1.74)	(8.53)	(6.08)
Liabilities	-7.4905***	-4.9257***	-2.4858**
	(-2.83)	(-3.52)	(-2.02)
Current Liabilities	18.1262***	8.6322***	4.2198**
	(4.84)	(4.37)	(2.42)
First-stage: IV_time	0.0016***	0.0016***	0.0016***
	(5.10)	(5.10)	(5.12)
First-stage F-statistic	26.06	26.06	26.18
Stock-Yogo 10% Critical Value	16.38	16.38	16.38
Anderson canonical LM statistic	26.09	26.09	26.21
Anderson LM p-value	0.0000	0.0000	0.0000
Cragg-Donald Wald F-statistic	26.06	26.06	26.18
Anderson-Rubin Wald Chi-sq	108.06	7.51	7.13
Anderson-Rubin Wald p-value	0.0000	0.0061	0.0076
Stock-Wright LM S statistic	107.25	7.53	7.15
Stock-Wright LM p-value	0.0000	0.0061	0.0075
Control	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	9546	9546	9537

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To comprehensively address the validity and reliability concerns raised by the IV estimations in Table 11 and 12, detailed first-stage regression results and diagnostic statistics are explicitly presented here. In the first-stage regression (taking column 1 in Table 11 as a representative example), the instrumental variable $IV\_distance$ demonstrates a strong and statistically significant positive correlation with the degree of firm's digital transformation (coefficient = 0.1077, t = 4.52, p < 0.001). The associated first-stage F-statistic is 20.43, which substantially exceeds the Stock–Yogo weak identification critical value of 16.38 (at the 10% maximal IV size), confirming that the instrumental variable is robustly correlated with firm digitalisation and not weak.

Regarding identification tests, the Anderson canonical LM statistic (Chi-squared = 20.47, p < 0.001) clearly rejects the null hypothesis of underidentification, confirming the instrumental variable effectively identifies the endogenous explanatory variable (Anderson, 2002). Moreover, weak-instrument-robust inference tests, including the Anderson–Rubin Wald test (Chi-squared = 90.41, p < 0.001) and Stock–Wright LM S test (Chi-squared = 89.90, p < 0.001), further validate the robustness of the IV estimates against potential weak instrument bias (Anderson & Rubin, 1949; Stock & Yogo, 2002).

Regarding the exogeneity of the software income as one component of the instrumental variable, although it could potentially influence firm performance indirectly through regional economic activity, this effect is substantially mitigated by explicitly including detailed firm-level control variables (e.g., size, leverage, profitability, growth, governance structures) and comprehensive fixed effects (firm and year). Consequently, residual direct effects on export performance are minimized, ensuring the instrumental variable primarily captures variation relevant to firm digitalisation.

These comprehensive diagnostics and clarifications robustly demonstrate that our IVs are indeed statistically and theoretically justified instrumental variables for firm's degree of digital transformation. The regression outcomes indicate that regardless of whether $IV\_distance$ or IV_time is used, the results are consistent with the main regression. This consistency confirms the robustness of our primary findings.

In summary, this section examines the robustness of the main regression analysis from four perspectives: (1) providing an alternative interpretation and measurement of the key dependent variable, export performance; (2) employing an alternative measurement for the key explanatory variable, digital transformation; (3) using the Generalized Method of Moments (GMM) instead of a high-dimensional fixed effects model to mitigate endogeneity issues and enhance estimation efficiency; and (4) utilizing instrumental variables to address endogeneity concerns. These four robustness checks collectively confirm the empirical design and the reliability and robustness of the empirical results of this study.

3.6. Discussion and Conclusions

This study explores the impact of digital transformation on export performance and its underlying mechanisms. First, a novel measure of digital transformation based on textual analysis was introduced. Subsequently, grounded in the Firm-Specific Advantages (FSAs) theory and the extended heterogeneous firm's theory discussed in Chapter 2, empirical tests demonstrated that digital transformation positively influences export performance and significantly enhances both capital efficiency and labour efficiency. These findings align with the FSAs theory's emphasis on the need for technology and human capital advantages in the digital era, as well as the extended general equilibrium model in the digital context discussed in Chapter 2.

Furthermore, mediation effect tests revealed that capital efficiency serves as a significant and robust mechanism. Although digital transformation significantly improves labour efficiency, the full-sample analysis did not support the hypothesis that enhanced labour efficiency further impacts export performance. Heterogeneity analysis indicated that the labour efficiency mechanism exists but is effective only in firms with inherently low labour efficiency. Additionally, the analysis revealed that when there is an imbalance in the development of capital efficiency and labour efficiency, allocating digital transformation resources to the weaker side yields greater benefits. This finding supports the optimal transformation ratio theory proposed in Chapter 2. Moreover, the heterogeneity analysis confirmed that digital transformation is not always beneficial, excessive digital transformation can lead to negative impacts when the additional benefits do not outweigh the costs.

Finally, a series of robustness tests, including alternative variables, alternative methods and instrument variables, are conducted to prove the reliability of the empirical results.

Overall, this study provides a detailed empirical analysis of the impact of digital transformation on export performance and its internal mechanisms. The key contributions of this study are as follows:

Firstly, this study develops a novel measurement approach for assessing the degree of digital transformation in firms based on textual analysis. Unlike previous literature that employed classification methods or used city-level digitalisation as a proxy, our method is precise to the firm-year level. It utilises keyword frequency in corporate annual reports, with weighted and adjusted keywords, providing a more detailed depiction of a firm's digital transformation. This method offers an exciting attempt at constructing variables based on natural language processing, which is hard to measure in traditional methods, paving the way for future research in this area.

Secondly, this study validates the mechanism by which digital transformation enhances export performance, providing empirical support for the theoretical model presented in Chapter 2. Additionally, our heterogeneity analysis reveals that the impact and mechanisms of digital transformation on export performance vary significantly based on the firm's initial levels of labour efficiency and capital efficiency. This finding introduces a new grouping criterion based on capital and labour efficiency levels when conducting academic research on firms, adding choices to traditional grouping criteria such as size, location, and state ownership of a firm.

Thirdly, from a practical perspective, the findings from Chapter 2 and the empirical analysis collectively demonstrate that digital transformation is not universally beneficial without drawbacks. While embracing digital transformation is inevitable for firms in the current wave of digitisation, it involves substantial upfront investments in resources and human capital. Therefore, firms must carefully balance the costs and benefits of digital transformation and allocate efficiency improvements judiciously.

Lastly, this study develops a set of instrumental variables based on commuting distance and time between geographic coordinates. The commuting distance-based instrumental variable overcomes the limitations of previous instruments that relied on straight-line distances, which must account for terrain and road conditions. The commuting time-based instrumental variable more accurately captures the effort required for movement between two locations. Empirical results indicate that these instrumental variables have significant potential for extension, providing a promising direction for future research on geographically based instruments.

However, this study has some limitations. First, due to the limited availability of corporate export customs data, the sample data only partially covers the most recent years, resulting in 9,682 valid observations. This limitation also hinders the ability to observe the long-term effects of digital transformation on export performance and efficiency improvements. Second, the heterogeneity analysis is constrained by the total sample size and the need to ensure effect identification in each subgroup. Consequently, the 2x2 grouping strategy is relatively coarse, precluding more detailed heterogeneity analyses and mechanism tests.

Future research can address these limitations by examining the long-term effects of digital transformation on export performance and efficiency improvements as more customs data becomes available. Additionally, in terms of methodology, more advanced and popular natural language processing techniques could be applied to analyse the mechanisms.

Chapter 4: The Pathway to International Expansion: Digital Transformation and Export Behaviour

Abstract

Based on panel data from Chinese listed companies, the study investigates the impact of digital transformation on firms' export diversification and export concentration. The theoretical analysis part distinguishes between two types of digital transformation using large language models, management digital transformation and production digital transformation, and discusses the theoretical explanations. The empirical results demonstrate that management digital transformation significantly increases firms' export diversification while reducing export concentration. In contrast, production digital transformation increases a firm's export diversification but has no significant impact on the export concentration.

This study provides empirical support for how different directions of digital transformation served as different types of resources and then had different impacts on firms' export behaviour. It suggests that firms should select digital transformation pathways that align with their specific needs. Furthermore, the findings highlight the importance for policymakers to guide directions of digital transformation in shaping firms' export behaviour.

Keywords: Management/Production Digital Transformation; Export Diversity; Export Concentration; Resource Based View.

4.1. Introduction

Digital transformation has been widely adopted in practice and extensively discussed in academic research (Feliciano-Cestero et al., 2023; Verhoef et al., 2021). In this study, digital transformation refers to the process by which firms leverage specific digital technologies, such as artificial intelligence (AI) or the Internet of Things (IoT), to implement targeted innovations in capital or human resources (Bharadwaj et al., 2013; F. Wang et al., 2023; F. Wang & Ye, 2023; Wessel et al., 2021) and then achieve specific organisational changes (W. Li & Li, 2022; Ramesh & Delen, 2021). However, there is limited research on the impact of digital transformation in the context of international business (AL-Khatib, 2023), especially in firm's export behaviour problems.

In terms of the research related to digital transformation, previous studies have largely focused on concept defining and value measuring, while other academic papers have explored its effects on firms' innovation (George et al., 2021; Melitz & Redding, 2021), productivity (Acemoglu & Restrepo, 2018b), financial costs and so on (G. Kim et al., 2011; F. Li, 2020). Following the research route of the literature, in the second chapter of this thesis, a general equilibrium model based on the classic heterogeneity firms model is developed to discuss the mechanism of how digital transformation has an effect on a firm's export performance (Krugman, 1979, 1980; Melitz, 2003). Then, based on the theoretical model, an empirical investigation of the effect of digital transformation on export performance is conducted in the third chapter (Adarkwah & Malonæs, 2022; F. Wang & Ye, 2023; Y. Wang et al., 2024). These two papers have discussed theoretically and empirically separately on how digital transformation has affected the export performance of the firms.

However, a critical issue still remains: the degree of digital transformation of firms was developed in a unified measurement (Alsheibani et al., 2018; Combes et al., 2012; Hoberg & Phillips, 2016; F. Wang & Ye, 2023), this approach often overlooks the heterogeneity among different firms (Camodeca & Almici, 2021; W. Zhang & Zhao, 2023). As highlighted in existing research and discussed in the previous two chapters, digital transformation encompasses diverse motivations, and firms exhibit varying emphases in their transformation efforts (Calderon-Monge & Ribeiro-Soriano, 2023; Feliciano-Cestero et al., 2023). Consequently, not all firms undertaking digital transformation follow an identical path (Gong & Ribiere, 2021; Kraus et al., 2021; Verhoef et al., 2021). This unsolved issue reveals a key research gap in the current literature—the lack of a detailed distinction in different ways of digital transformation undertaken by firms (Nadkarni & Prügl, 2021). In this chapter, we first address this gap by utilizing refined text analysis techniques to identify two directions of digital transformation, which can be defined as production digital transformation and management digital transformation. However, merely distinguishing between the different directions of digital transformation does not provide substantial academic value or practical guidance; it is crucial to further investigate whether these two directions of digital transformation make a difference in the impacts on firms (Jedynak et al., 2021).

Meanwhile, in terms of the specific effects digital transformation has on firms, previous literature has thoroughly examined various kinds of effects (D. Chen et al., 2022; Hanelt et al., 2021; J. Li et al., 2022), including the theoretical and empirical analysis of its influence on export performance (F. Wang et al., 2023; F. Wang & Ye, 2023; B. Zhang et al., 2024). However, in terms of export choices, there has been limited research on how digital transformation affects firms' export behaviour (Haddoud et al., 2021; Lu et al., 2017). The export behaviour of the firms is worthwhile studying because it affects both micro-level business management practices and macro-level national trade patterns (Erbahar & Rebeyrol, 2022; Felbermayr & Jung, 2011; L. Zhang et al., 2022). Understanding export behaviour provides insights into a firm's performance in foreign markets (Impullitti et al., 2013; Melitz, 2003). Thus, combined with the first objective, the second core objective of this paper is to examine how different directions of digital transformation, as previously categorized, could influence firms' export behaviour. This paper narrows down the behaviour to two specific export patterns, particularly export diversification (the number of countries a firm exports to) (Fabling & Sanderson, 2013; Krugman, 1980; Melitz, 2003) and export concentration (the extent to which exports are concentrated in a few countries versus distributed across multiple destinations) (Dichtl et al., 1984; Fernandes et al., 2019). By analysing these patterns, this study aims to offer valuable academic insights and practical implications for both business managers and policymakers, given that firms' export decisions can collectively shape a nation's overall trade profile (De Sousa et al., 2020; Gupta & Chauhan, 2021).

The key contributions of this study can be summarized as follows:

First, this study provides a clear distinction between management digital transformation and production digital transformation, offering a more nuanced understanding of how each of them impacts on firms, which is a key aspect often overlooked in existing literature (Sklenarz et al., 2024; Y. Wang et al., 2024; B. Zhang et al., 2024).

Second, by applying the Resource-Based View (RBV) framework, this study demonstrates that management digital transformation strengthens firms' organizational and decision-making capabilities, enabling them to enter more international markets and reduce dependency on a few core markets (D. Chen et al., 2022; Sultana et al., 2022; Yadav et al., 2023), thus increasing export diversification and decreasing the export concentration. Production digital transformation, on the other hand, primarily enhances production efficiency and product customization, which supports export diversification but has limited influence on export concentration (Ashaari et al., 2021; Okorie et al., 2023).

Finally, this research provides practical insights for firms and policymakers. Firms are encouraged to adopt digital transformation strategies that align with their resources and market goals, while policymakers can guide the firm's export behaviour by encouraging particular direction of digital transformation (de los Reyes, 2019; Tian et al., 2023; Viard & Economides, 2015).

By addressing these dimensions, this study adds to the growing body of literature on digital transformation and its impact on firms' export performance, offering valuable implications for both academic research and strategic decision-making in a rapidly digitalizing global economy.

4.2. Theoretical Background and Hypothesis Development

4.2.1. Decomposition of Digital Transformation

In previous research, digital transformation has often been treated as a broad concept (Angelopoulos et al., 2023), encompassing a comprehensive shift in a firm's production, management, and other operational areas (Feliciano-Cestero et al., 2023). A common sense in the literature related to digital transformation shows that digital transformation is not only a form of technological advancement but also provides significant theoretical contributions by capturing the multifaceted nature of changes within firms (Gong & Ribiere, 2021; Markus & Rowe, 2021; Roth, 2019). The inherent complexity of digital transformation presents significant challenges for precise measurement. In contemporary empirical research, the degree of digital transformation is often assessed and analysed using a standardised approach across all firms, despite substantial differences among the firms not being evaluated (Y. Yang et al., 2023; Yue, 2023; W. Zhang &

Zhao, 2023). This standardised process provides the possibility to compare the degree of digital transformation and corresponding outcomes across different firms. As discussed in Chapter 3, employing text analysis to capture the degree of digital transformation allows for a clearer identification of a firm's digital transformation activities (Buyanova et al., 2022; Schnasse et al., 2021). However, this research approach tends to overlook the inherent differences among firms (Nadkarni & Prügl, 2021; Zhu, Ge, et al., 2021). Companies naturally vary significantly in terms of scale, strategic direction, business strategies, and operating environments (Clemente-Almendros et al., 2024; Gao et al., 2023). Applying a single standard to measure digital transformation across all firms is inherently biased (J. Yang et al., 2024).

To address this limitation, it is necessary to decompose digital transformation into more specific dimensions, which can more accurately capture the diversity of firms' transformation efforts. Therefore, in this study, building on the text analysis method proposed in Chapter 3 for measuring digital transformation (Hoberg & Phillips, 2016), we attempt to further refine the direction of digital transformation efforts within firms. Specifically, we employ a large language model (LLM) to classify 49 keywords related to digital transformation (Arslan et al., 2021; M. Liu & Shi, 2024).

Based on the definitions and some classifying explorations (Nadkarni & Prügl, 2021). A firm's digital transformation can be identified in two main aspects. The first one is the kind of digital transformation that refers to technological advancement (Loebbecke & Picot, 2015), which is highly related to the production process, so is defined as production digital transformation. The second one is concerned with the digital transformation that changes are driven by the actors, for example, the managerial and organizational capabilities (L. Li et al., 2018; Nadkarni & Prügl, 2021), in our context, we name it as management digital transformation. In summary, production digital transformation is closely connected to higher efficiency, better product quality and lower production costs. Management digital transformation is related to the ability to allocate resources. After defining the two types of digital transformation, we then assess the degree to which firms implement each type of digital transformation.

Specifically, this study employs a large language model (LLM), deepseek-llm-67b-base, which has been specifically fine-tuned for semantic understanding of the Chinese language, to classify the keywords into production and management digital transformation. Initially, we provided the LLM with explicit definitions of two directions of digital transformation under the context of this study. Subsequently, we inputted the set of 49 keywords identified within our analysis and instructed the LLM to classify each keyword accordingly.

Given the inherent practical challenges in precisely distinguishing between production and management digital transformation, a few keywords inevitably fell within ambiguous boundaries. To address this ambiguity, instead of binary classification method, the LLM was explicitly instructed to assign each keyword a score between 0 and 1, indicating the degree to which the keyword aligns with either production or management digital transformation. Based on these scores, keywords clearly aligned with either category were assigned a 100% weighting under their respective classifications. In contrast, for keywords lacking clear categorical distinction, we allocated a 50% weighting to both categories. Under our method, these ambiguous keywords are considered as equally contributing to both production and management digital transformation measurements.

Moreover, considering the potential instability inherent in large language model outputs, we repeated the entire classification process independently ten times using the same LLM agent, with identical context provision and classification instructions, to ensure rigorousness. The final classification for each keyword was then determined by selecting the categorization that appeared most frequently across the ten iterations. This process established the definitive classification adopted by this study, specifying whether each keyword belonged predominantly to production digital transformation, management digital transformation, or equally to both.

4.2.2. Digital Transformation Under RBV

Considering the nature of digital transformation involved with a firm's competitive advantage (Calderon-Monge & Ribeiro-Soriano, 2023), This research addresses the classic Resource-Based View (RBV) to analyse the implementation theoretically. Since the inception of the Resource-Based View, academic literature has consistently emphasised that a firm's competitive advantage is derived from its tangible and intangible resources (Barney, 1991, 2001; Elia et al., 2021). However, these studies also underscore that merely possessing these resources is insufficient; firms must effectively reorganize and coordinate them to convert these resources into a sustainable competitive advantage (Amit & Schoemaker, 1993; Peteraf et al., 2013). In terms of specifically concerning digital transformation and exports, existing research has explored the benefits and costs associated with digital transformation for exporting firms and examined how the quantity and quality of resources influence digital export activities (Elia et al., 2021).

Moreover, in theoretical and empirical research that considers digital capabilities as a form of corporate resource, much of the literature has focused on the impact on small and medium-sized enterprises (SMEs) (Gregory et al., 2019; Schu et al., 2016). The rationale provided by these studies is that SMEs, compared to larger firms, often struggle to allocate sufficient resources to adopt digital technologies and therefore face greater challenges in achieving a competitive advantage (Hånell et al., 2019; Tolstoy et al., 2021). At the same time, due to their smaller size, SMEs tend to be more agile and flexible in adapting their business models and operations, potentially creating new opportunities to gain a comparative advantage (Clemente-Almendros et al., 2024). Almost all these studies treat digital transformation as a unified resource and analyse its impact on firms but didn't manage to identify that digital transformation can provide heterogeneous degrees of comparative advantages in various dimensions, which is the key gap we attempt to fill in this paper.

Although Chapter 3 and Chapter 4 of this thesis address related overarching research questions, namely, the impacts of digital transformation on firms' export performance, the theoretical lenses employed differ due to distinct analytical emphases and specific research focuses. In Chapter 3, the Firm-Specific Advantages (FSAs) theory was utilized primarily because the focus was explicitly on how digital transformation enhances firms' specific advantages, thereby strengthening their international competitiveness in export markets. FSAs theory emphasizes firm heterogeneity explicitly in the context of comparative advantage and international trade.

In contrast, Chapter 4 adopts the Resource-Based View (RBV) as its underlying theoretical framework. The RBV focuses explicitly on the internal resources and capabilities of the firm, arguing that competitive advantage stems from firm-specific resources that are valuable, rare, inimitable, and non-substitutable (VRIN). Chapter 4 particularly distinguishes two internal resource dimensions arising from digital transformation: management DT (organizational and strategic resources) and production DT (operational and technological resources). The RBV theory provides a robust and nuanced theoretical foundation to understand how these distinct internal resource categories differently influence firms' export diversification and concentration.

4.2.3. Export Behaviours

A considerable body of study has focused on firms' export behaviours, particularly their entry into and exit from foreign markets (Fabling & Sanderson, 2013; Haddoud et al., 2021; Impullitti et al., 2013). Findings indicate that a firm's export activities are strongly associated with its production efficiency and domestic performance (Fernandes et al., 2019). Additionally, studies have highlighted the importance of a firm's ability to acquire local information for successful market entry (Ashaari et al., 2021; Jadhav et al., 2023). For firms, understanding local consumer characteristics, legal regulations, and cultural norms is crucial for entering and succeeding in international markets (De Sousa et al., 2020; Dichtl et al., 1984; Haddoud et al., 2021).

Many studies have linked firms' entry and exit behaviours to the Resource-Based View (RBV), which argues that a firm's resources and capabilities significantly influence its competitiveness in foreign markets (Elia et al., 2021; Madhani, 2010; Wójcik, 2015). According to this perspective, a firm's ability to enter international markets depends on the extent of its resource base (Martens, 2013). Similarly, firms with unique resources are more confident in operating within highly uncertain foreign markets and are more inclined to take risks and adopt aggressive business strategies (Martín Martín et al., 2022; Sharfaei et al., 2023). Furthermore, several studies have extended the RBV by incorporating a knowledge-based perspective, suggesting that firms can leverage technology and knowledge of international markets to enhance their ability to enter new markets and expand their export activities (Alon et al., 2018). Although this approach introduces a new dimension to the concept of resources, it aligns with the traditional RBV by recognizing knowledge as a vital corporate resource (Dhanaraj & Beamish, 2003). Moreover, some studies emphasise that a firm's ability to enter foreign markets is the result of multiple interacting factors rather than reliance on a single resource (Ramon-Jeronimo et al., 2019). These studies consistently emphasise that a firm's capacity to penetrate international markets largely depends on its resources and the ability to effectively utilise them (Elia et al., 2021a). This perspective supports the argument that digital transformation can serve as a core resource for firms seeking to expand into global markets (Helfat & Lieberman, 2002).

Based on the literature related to the export behaviour of firms, the entry and exit behaviour is broadly considered a key proxy indicator (Impullitti et al., 2013). However, the entry and exit actions are relatively micro-level and are more suited to analysing a firm's entry and exit from a single market (Haddoud et al., 2021; Martín Martín et al., 2022). When a firm exports to multiple countries, these indicators may struggle to capture shifts in the firm's export preferences accurately

(Fabling & Sanderson, 2013). Therefore, this paper introduces two macro-level indicators to assess firm export behaviour: export concentration and export diversification, which are better equipped to capture the characteristics of a firm's behaviour when engaging with multiple export markets.

4.2.4. Hypothesis Development

Building on the literature discussed above, this paper focuses on how digital transformation impacts firms' export diversification and export concentration—both critical dimensions of a firm's export behaviour and strategy. The analysis is primarily grounded in the Resource-Based View (RBV), which highlights the pivotal role of firm-specific resources in shaping competitive advantage (Elia et al., 2021). Given that digital capabilities are increasingly regarded as essential resources for firms operating in global markets, RBV provides a robust theoretical framework for examining the effects of digital transformation (Madhani, 2010).

In the previous chapter, we employed the Firm-Specific Advantage (FSA) theory to examine the impact of digital transformation on firms' export performance. The focus of that chapter is firms' external performance, which is closely related to their comparative advantages in international markets, making using FSA theory appropriate. In contrast, the current chapter concentrates on the internal direction of firms' digital transformation. Since the direction of a firm's transformation is intimately connected to the specific resource dimensions provided by digital transformation, it is more fitting to utilise the Resource-Based View (RBV) theory in our discussion of internal transformational strategies within firms.

According to the Resource-Based View (RBV), digital transformation can provide firms with unique and irreplaceable resources, enabling them to enter new markets and enhance their export diversification (Barney, 1991). There are several aspects of the benefits of exporting more diverse. First, like asset allocation, a higher degree of export diversification means that firms can access more destinations and a larger pool of export choices. The advantage of having more options becomes most apparent when facing economic shocks (Qian & Mahmut, 2016). When the market environment becomes worse in specific markets, firms with diversified exports can redirect their products and services to alternative destinations (Nguyen & Schinckus, 2023; Vannoorenberghe et al., 2016). Moreover, the resources that facilitate a firm's accessibility to a broader range of markets are complex for competitors to replicate (Ramon-Jeronimo et al., 2019). Digital transformation constitutes such a unique and irreplaceable resource for firms. By adopting digital technologies like big data analytics, artificial intelligence (AI), and cloud computing, firms develop capabilities that enhance the efficiency and effectiveness of market entry processes (Okorie et al., 2023). These digital capabilities allow firms to understand market demands better, optimize supply chains, and improve communication with international clients—all critical factors in gaining access to diverse markets.

Therefore, digital transformation can enhance a firm's export diversification by lowering barriers to entry into new markets. Firms that adopt digital transformation strategies can leverage digital marketing platforms and e-commerce solutions to reach customers in geographically distant or previously inaccessible markets (Tolstoy et al., 2021). Additionally, integrating digital supply chain management tools enables firms to efficiently manage logistics and distribution across multiple countries efficiently, further facilitating export diversification (Gregory et al., 2019; Tian et al., 2023). As firms diversify their export destinations, they reduce reliance on single markets, enhancing resilience to economic fluctuations or trade restrictions in specific regions (Impullitti et al., 2013). This aligns with the broader RBV argument that firms with a diversified resource base are better positioned to handle uncertainty and maintain competitive advantages in dynamic environments (Elia et al., 2021). Firms with advanced technological capabilities from digital transformation are more likely to succeed in diverse export markets due to their ability to adapt to varying market conditions and regulatory environments (Fernandes et al., 2019).

Based on the above reasoning, we propose the following hypothesis:

H1a: Digital transformation enhances firms' Export Diversification Index.

As previously discussed, digital transformation enhances firms' export diversification, providing them with greater accessibility to a broader range of export destinations. However, increased export accessibility does not necessarily lead to an improved distribution of exports. The impact of digital transformation on export concentration—a proxy index that reflects how evenly exports are distributed across multiple destinations—offers insight into firms' export preferences (Dichtl et al., 1984; Fabling & Sanderson, 2013).

For firms, distributing exports more evenly across accessible markets can effectively mitigate the risks associated with economic fluctuations. In this context, digital transformation provides crucial resources that enable firms to optimize their market portfolios. For example, predictive analytics and machine learning tools help firms identify opportunities in underdeveloped or emerging regions, encouraging them to allocate exports more efficiently across various countries (D. Chen et al., 2022; Schu et al., 2016). By leveraging these technologies, firms can reduce their reliance on a limited number of markets, thereby decreasing export concentration.

Therefore, we hypothesize that digital transformation can decrease a firm's Export Concentration Index. By adopting digital strategies, firms enhance their capabilities to explore and penetrate multiple markets more evenly, aligning with the RBV argument that firms with diversified resources are better positioned to handle uncertainty and maintain competitive advantages (Elia et al., 2021).

Based on the above reasoning, we propose the following hypothesis:

H1b: Digital transformation decreases firms' Export Concentration Index.

Up to now, our discussion of the research hypotheses concerning digital transformation's impact on firms' export diversification and concentration has been relatively general. However, as previously noted, employing a broad definition of digital transformation significantly overlooks the heterogeneity among firms in their implementation processes—specifically, the focus between production digital transformation and management digital transformation. The effects resulting from these two focal areas may differ considerably. Thus, such differentiation is essential for understanding the nuanced impacts of various digital transformation strategies on export diversification (Ramesh & Delen, 2021; Roth, 2019).

Fundamentally, the direction a firm takes in its digital transformation provides distinct resources, which may, in turn, lead to different impacts on its export behaviour (Dhanaraj & Beamish, 2003). The key resource management digital transformation can provide could be categorized as organizational resources. This could allow firms to get more information in a particular market and have the ability to access that market. These technologies could enhance information processing, improve decision-making efficiency, and facilitate cross-departmental collaboration (Okorie et al., 2023).

By engaging in management digital transformation, firms can gather real-time information on global market demand, consumer preferences, and industry trends, enabling them to adjust their export strategies more flexibly and enter new markets (Sultana et al., 2022). For instance, big data analytics assist firms in identifying potential opportunities in international markets, while cloud computing allows for swift deployment of products and services, reducing the costs and risks associated with entering new markets (Ashaari et al., 2021). These capabilities align with the RBV's emphasis on digital management resources to expand export markets and enhance export diversification. Therefore, we infer that management digital transformation can increase a firm's export diversification. Based on this analysis, we propose the following hypothesis:

H2a: Management digital transformation increases a firm's export diversification.

Similarly, from a theoretical standpoint, production digital transformation positively affects firms' export diversification. Whether through the adoption of the Internet of Things, intelligent manufacturing, or industrial Internet systems, these technologies fundamentally assist firms in enhancing production efficiency via automation and customization (Vo-Thanh et al., 2022). Improved product quality or lower cost enables firms to enter new markets (C. S. A. Cheng et al., 2020; Combes et al., 2012; Fabling & Sanderson, 2013), while enhanced production efficiency allows them to meet the increased export demand that arises after expanding into new markets (Gao et al., 2023; Hossain et al., 2022). The resources such as improved product quality or reduced production costs are categorized as technological resources, and can be transformed into firms' comparative advantages in international markets (Dhanaraj & Beamish, 2003; Elia et al., 2021; Madhani, 2010). These advantages enable firms to expand their sales markets, leading to greater export diversity. Therefore, regarding firms' production digital transformation, we propose the following research hypothesis:

H2b: Production digital transformation increases a firm's export diversification.

Unlike the Export Diversification Index, the impacts of management digital transformation and production digital transformation on export concentration may differ significantly.

A firm's export concentration index directly reflects the distribution of its exports across different destinations (Fabling & Sanderson, 2013; Hossain et al., 2022). At this level, management digital transformation provides core organizational resources such as more accurate and real-time information and an enhanced ability to convert this information into strategic decisions (Barney, 1991; Gregory et al., 2019; Helfat & Lieberman, 2002; Martín Martín et al., 2022). The firm's export concentration will illustrate this improved decision-making capability. From a risk perspective, a lower export concentration can significantly reduce a firm's export risks and enhance its ability to withstand economic shocks (AL-Khatib, 2023; Y. Yang et al., 2023).

Additionally, a lower export concentration indicates that the firm is making fuller use of expanded export markets. Firms with management digital transformation have the capability to identify the potential opportunities in emerging and new markets (Alon et al., 2018; Haddoud et al., 2021; Hånell et al., 2019). Therefore, we hypothesize that management digital transformation can significantly help firms reduce reliance on a few export destinations, diversify their product exports more broadly, and then reduce their export concentration (Madhani, 2010).

In contrast, production digital transformation focuses on technologies and resources related to product quality, cost, and the efficiency of producing products (AlNuaimi et al., 2022; Amiri et al., 2023; Peteraf et al., 2013). These enhancements help firms achieve higher comparative advantages at the product level and enable their products to enter more markets (Mariani & Nambisan, 2021; Martens, 2013). However, the resources provided by production digital transformation do not assist firms in better allocating their export destination portfolios. Even if superior product quality or lower costs allow firms to develop new markets, they may lack the capability to make full use of these opportunities (De Sousa et al., 2020; Fernandes et al., 2019). The resources required to fully leverage expanded markets are supplied by management digital transformation. Therefore, we hypothesize that production digital transformation does not have a significant impact on firms' export concentration (Gao et al., 2023; Hossain et al., 2022; Impullitti et al., 2013):

H3a: Management digital transformation reduces a firm's export concentration.

H3b: Production digital transformation has no significant effect on the firm's export concentration.

In summary, these six hypotheses explore the distinct impacts of management and production digital transformation on firms' export behaviour. H1a suggests that digital transformation can enhance a firm's export diversification. H1b proposes that digital transformation can decrease a firm's export concentration. H2a posits that management digital transformation specifically increases export diversification by improving decision-making and market entry efficiency, while H2b argues that production digital transformation achieves similar outcomes by enhancing the comparative advantage of the products. H3a suggests that management digital transformation reduces export concentration by promoting a more balanced distribution of exports across markets, whereas H3b indicates that the effects of production digital transformation on export concentration are not significant.

The Structure of the study and the hypotheses are illustrated in Figure 13.

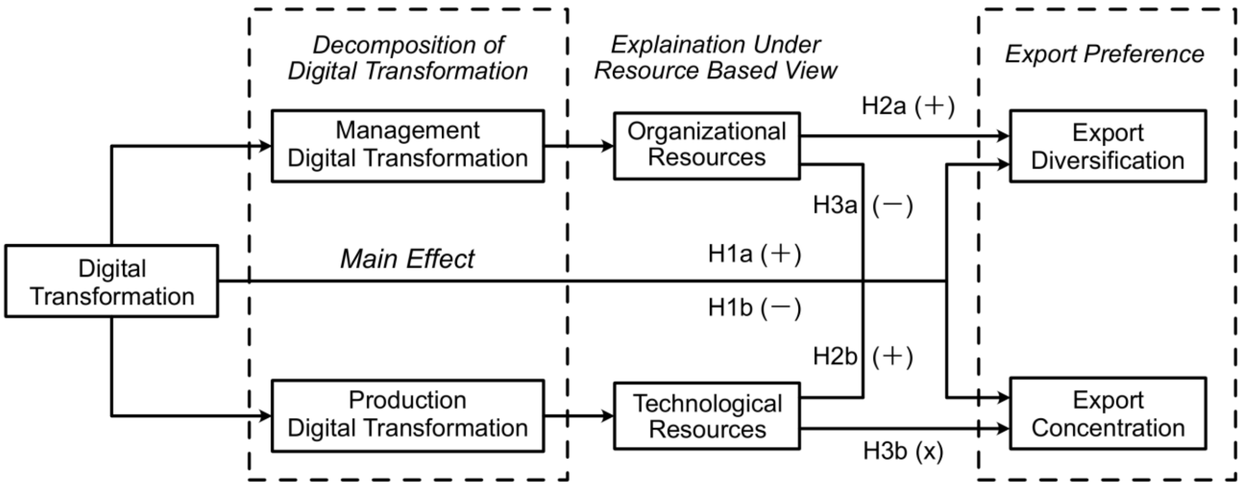


Figure 13. The structure of the study

4.3. Research Design

4.3.1. Methodology

In terms of the methodology, we first conducted a literature review to synthesize and analyse existing studies (Snyder, 2019). This was followed by a theoretical analysis discussing how resource-based theory should be reinterpreted in the context of digital transformation. We then explored the application of this revised theoretical framework to future studies on digital transformation. For the empirical analysis, we employed a high-dimensional fixed effects model with clustered robust standard errors to ensure the reliability of our findings (Guimarães & Portugal, 2010). Additionally, based on the baseline results, we decomposed the digital transformation into two distinct directions called management digital transformation and product digital transformation to conduct further analysis. After that, we performed a series of robustness checks to validate the consistency and reliability of our empirical results. Finally, we analysed the results and proposed academic and practical implications.

The methodology of the paper is illustrated in Figure 14.

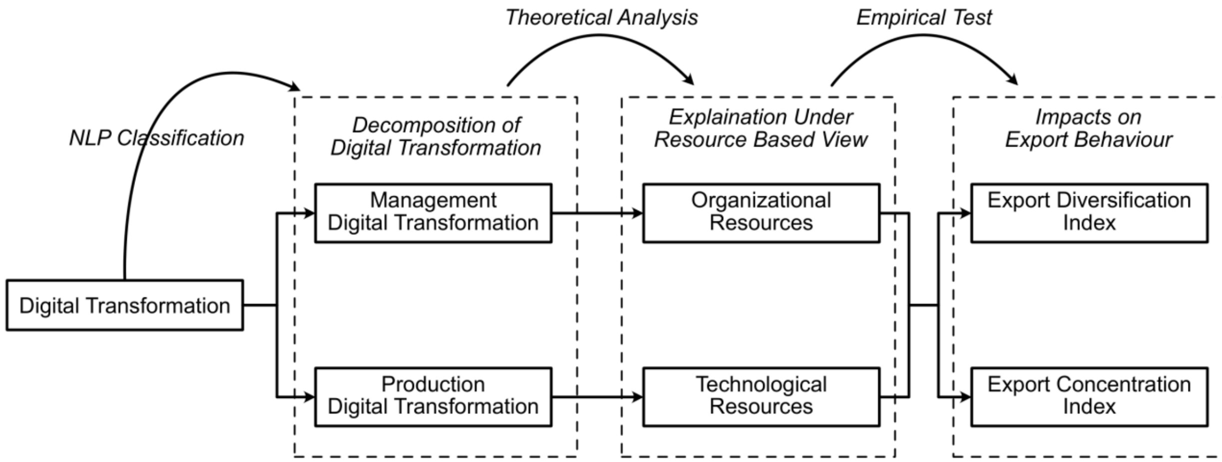


Figure 14. The methodology of the study

4.3.2. Sample and Data

To examine the changes in firms' export behaviours following digital transformation, we employed a quantitative analysis approach to test our research hypotheses. Firstly, we investigated whether digital transformation leads to significant changes in firms' export diversification and export concentration (H1a and H1b). These findings serve as our baseline results, providing a reference for subsequent analysis and discussion. Following this, we differentiated between management digital transformation and production digital transformation, assessing their respective impacts on firms' export diversification and concentration (H2a, H2b, H3a, and H3b). Finally, we conducted further analysis to explore the underlying reasons for these outcomes. Robustness checks were also performed to ensure the reliability of our findings.

Regarding the data, our study draws on four primary sources. First, data on digital transformation were obtained from the annual reports of publicly listed Chinese companies. These data contain the full text of the annual report, the list of subtracted keywords related to digital transformation, as well as the weight of them calculated by TF-IDF algorithm. Then, the text data was also used to categorise and construct proxy variables for management and product digital transformation. Second, export data were sourced from the China Customs database, which provides detailed records of Chinese industrial firms' export activities, including the destination countries and corresponding export volumes for each firm. Third, geographic data between China and other countries were collected from Google Maps API, enabling us to better understand firms' export patterns. Finally, financial data were extracted from the CSMAR database, which includes comprehensive financial indicators and key firm-level variables, most of which were used as control variables in this study. For a few variables not covered by the database, we manually computed them using structured data from firms' financial statements.

In terms of sample construction, due to the availability of publicly released Chinese customs data only up to 2016, this part matched this data with digital transformation information of listed firms and retained as many valid observations as possible. The resulting dataset covers the period from 2010 to 2016. To ensure the completeness and reliability of financial information, the sample is limited to publicly listed companies, excluding those in the financial sector as well as firms classified by the China Securities Regulatory Commission (CSRC) as requiring special treatment due to potential risks to investors. After further excluding observations with missing data, the final dataset consists of 9,526 valid firm-year observations. It is important to note that although efforts were made during data processing to retain as many observations as possible, the limited availability of customs data imposes a clear constraint on sample size. As a result, the findings of this study may have limitations in terms of generalizability. Caution should be exercised by researchers and policymakers when extending these results to broader contexts.

4.3.3. Dependent Variables

Export Diversification Index

In our research, export diversification is considered a crucial indicator for measuring the scope of a firm's export markets (De Sousa et al., 2020; Haddoud et al., 2021). For a company, the extent to which its products and services are exported reflects the size and range of its business operations. A greater export breadth indicates that a firm's business reaches a wider array of international markets and suggests a higher level of global recognition (Impullitti et al., 2013). Within the context of export markets, the number of countries to which a firm export significantly reflects its export diversification. Therefore, we use the number of destination countries as a proxy variable to represent a firm's export diversification (Vannoorenberghe et al., 2016).

Export Concentration Index

When firms engage in export activities, they must not only consider whether the number of export destinations has effectively increased but also whether the distribution of exports across different countries has changed. Based on this approach, we developed an export concentration index, which is similar to the Herfindahl Index commonly used to measure industry concentration (Rhoades, 1993). In our study, we first identified each firm's annual export volume to each country.

We then calculated the proportion of a firm's exports to each country relative to its total exports. By summing the squares of these proportions across all countries, we derived the firm's Export Concentration Index (ECI), which reflects the concentration of its exports. The formula for calculating the export concentration of firm i in year t is as follows:

$$ECI_{it} = \sum_{j=1}^{N} \left(\frac{X_{itj}}{X_{it}}\right)^2$$

Where:

X_{itj} represents the export volume of firm i to country j in year t.

X_i denotes the total export volume of firm i in year t (i.e., the sum of exports to all countries).

N is the total number of countries to which the firm exports.

According to our definition, the Export Concentration Index (ECI) ranges from 0 to 1. An ECI value close to 1 indicates that the firm's exports are highly concentrated in a few countries, whereas an ECI value close to 0 suggests that the firm's exports are more diversified across a wide range of markets.

4.3.4. Independent Variables

The degree of a firm's digital transformation is a central metric in this thesis, with its measurement methodology thoroughly discussed in Chapters 2 and 3. In brief, we employ text analysis techniques to extract relevant information from firms' annual reports. Specifically, we identify keywords related to digital transformation and determine their relevance based on weights derived from the Digital Transformation White Paper published by Chinese enterprises. Subsequently, we apply the TF-IDF (Term Frequency-Inverse Document Frequency) algorithm to weight these keywords, enabling us to calculate a composite score that serves as a proxy for the firm's level of digital transformation.

Management Digital Transformation

While the impact of digital transformation on export performance has been extensively discussed in earlier chapters, this paper takes a step further by differentiating digital transformation into two distinct categories based on the direction of implementation across various firms: management digital transformation and production digital transformation. Management digital transformation involves integrating and utilising digital technologies—such as cloud computing, big data analytics, blockchain, enterprise resource planning (ERP) systems, and supply chain management (SCM) systems—to optimize management processes, enhance decision-making efficiency, and strengthen data-driven management capabilities. The ultimate aim is to achieve more transparent, refined, and intelligent management, thereby improving overall management effectiveness.

Specifically, the impact of management digital transformation at the enterprise level includes several key aspects. By collecting, storing, and analysing vast amounts of business data, company management can make more scientific and practical decisions based on real-time information. Big data and artificial intelligence technologies aid in identifying potential business opportunities and risks. Implementing ERP systems, customer relationship management (CRM) systems, and supply chain management systems as part of the digital transformation efforts can optimize and integrate various management processes, eliminate information silos, and facilitate information sharing and collaboration across departments, ultimately enhancing management efficiency. Additionally, digital technologies enable the intelligent allocation and dynamic adjustment of various corporate resources (such as human resources, finance, and materials) to maximize resource utilization and reduce operational costs. Technologies like blockchain can further enhance governance transparency, strengthen internal process control and compliance management, and mitigate fraud and misconduct risks.

To operationalize the concept of management digital transformation, we categorized 49 keywords related to digital transformation using a large language model (LLM). From this, 29 keywords were identified as relevant to management digital transformation. By weighting these keywords and aggregating their presence in annual reports, we derived an indicator representing the level of a firm's focus on management in its digital transformation efforts. In our dataset, a higher management digital transformation index indicates greater investment in management-oriented digital transformation activities.

Production Digital Transformation

In contrast, production digital transformation refers to the application of advanced digital technologies and tools—such as the Internet of Things (IoT), smart manufacturing systems, industrial internet, intelligent robots, cloud computing, and big data analytics—to optimize and enhance the efficiency and effectiveness of production processes. The core objective of production digital transformation is to increase automation, reduce production costs, improve product quality, and enhance output efficiency, thereby boosting a firm's market competitiveness. This transformation encompasses several areas: the use of intelligent robots, automated control systems, and artificial intelligence to automate production processes, which not only reduces reliance on manual labour but also improves production speed and precision. IoT and big data analytics enable firms to monitor real-time data from the production process (such as equipment status and environmental parameters) and dynamically optimize based on this data, increasing the flexibility and responsiveness of production lines. Digital tools also optimize resource allocation and usage, reducing energy consumption and material waste while improving overall resource efficiency. Additionally, production digital transformation includes the flexible adjustment of production processes to meet market demands for personalized and customized products, making small-batch, multi-variety production feasible.

Similarly, among the 49 keywords related to digital transformation, we used an LLM model to identify 20 keywords pertinent to production digital transformation. These keywords were then weighted and processed using the TF-IDF algorithm to create a proxy indicator for a firm's level of production digital transformation.

4.3.5. Control Variables

In this analysis, a set of control variables is included to account for various aspects of firm characteristics and financial structure, each defined and quantified as follows:

Profitability and Efficiency: ROA (Return on Assets): ROA is calculated as net profit divided by the average total assets during the year. It measures how efficiently a company is using its assets to generate profit. Including ROA as a control variable is essential because more profitable firms may have more resources to invest in digital transformation and expanding export activities. ATO (Asset Turnover Ratio): This is calculated as revenue divided by average total assets. It reflects how efficiently a company generates sales from its asset base. Higher asset turnover could imply better operational efficiency, which can influence a firm's export strategy. It is included to account for firms' operational efficiency in the analysis. Cashflow (Cash Flow Ratio): Defined as net cash flow from operating activities divided by total assets. This ratio measures liquidity and a firm's ability to generate cash relative to its asset base. Firms with better cash flow may have more flexibility in managing operational and international expansion activities, making it an important control variable.

Financial Structure and Leverage: LEV (Leverage): Leverage is defined as total liabilities divided by total assets at year-end. This ratio indicates the extent to which a company is financing its operations through debt. Higher leverage could limit a firm's flexibility in undertaking new investments or expanding into international markets, making it a crucial control variable for understanding export behaviour. Liability: Total liabilities reflect the overall debt burden of the firm. This provides an absolute measure of the firm's financial obligations, controlling for the extent to which firms with higher debt levels are more constrained in expanding into new markets. Cliability (Current Liabilities): Current liabilities are a measure of short-term financial obligations. It is important to control for current liabilities as it reflects the firm's immediate liquidity needs, which may impact its ability to invest in long-term digital transformation projects or export diversification.

Growth and Market Valuation: Growth (Revenue Growth Rate): This is calculated as (current year revenue - previous year revenue) / previous year revenue. It indicates the rate at which a firm is expanding its sales, providing insight into the firm's growth trajectory. Growth is an important control because rapidly growing firms may be more inclined to engage in digital transformation and expand their export markets. BM (Book-to-Market Ratio): The book-to-market ratio is defined as the book value of a company divided by its market value. A higher BM ratio may indicate that a firm is undervalued, possibly affecting its investment decisions in digital transformation and global market expansion. Including this ratio as a control variable accounts for differences in market valuation. PB (Price-to-Book Ratio): The price-to-book ratio (PB) compares a firm's market value to its book value. A lower PB ratio may signal that the market perceives the company as less innovative, which could influence its capacity for digital transformation and export strategies. This is important to control for differences in market perceptions across firms.

Governance and Ownership Structure: Indep (Board Independence Ratio): Defined as the ratio of independent directors to the total number of directors. A higher proportion of independent directors is often associated with better governance and decision-making, which can influence a firm's strategic choices, including digital transformation and export expansion. Top1 (Largest Shareholder Ownership): These variable measures the ownership stake of the largest shareholder as a percentage of total shares outstanding. A high concentration of ownership may affect the firm's governance and investment strategies, potentially influencing its digital transformation initiatives and export behaviour. SOE (State-Owned Enterprise): This is a binary variable, where 1 represents state-owned enterprises and 0 represents privately owned firms. SOEs often have different strategic objectives and access to resources compared to private firms, which can affect their propensity to invest in digital transformation and expand internationally. Controlling for SOE status is important to differentiate between ownership types.

Firm Characteristics: Firmage (Firm Age): Firm age is calculated as the natural logarithm of (current year - year of establishment + 1). Older firms may have more established processes and market relationships, while younger firms may be more agile and innovative. Firm age is included to control for the effect of organizational maturity on export activities and digital transformation.

These control variables ensure that the analysis captures firm-specific characteristics such as financial performance, operational efficiency, governance, and market positioning, all of which can influence the relationship between digital transformation and export behaviour.

4.3.6. Empirical Test Design

Given that the data used in this study is panel data, encompassing multiple firms over an extended period, each firm may exhibit unique, unobservable characteristics. To address this issue and account for the longitudinal nature of the dataset, we employ a high-dimensional fixed effects model, which is well-suited for capturing firm-specific effects that remain constant over time. Additionally, to further mitigate potential estimation bias caused by cross-industry variations, we use robust standard errors clustered at the industry level, ensuring greater accuracy in our empirical results. The regression model for Hypothesis 1 is specified as follows:

$$EDI_{it} = \beta_0 + \beta_1 Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

$$ECI_{it} = \beta_0 + \beta_1 Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

Where:

EDI_{it} is one of the core independent variables, referring to the export diversity index of the firm i on year t.

ECI_{it} is the second core independent variable, referring to the export concentration index of the firm i on year t.

$Digital_{it}$ is the core dependent variable, referring to the degree of digital transformation of the firm i on year t.

$Control$ are the predefined control variables of the regression.

α_i represents the firm fixed effects.

γ_t represents the time fixed effects.

ϵ_{it} is the error term clustered by industry.

The regression models for Hypotheses 2 and 3 follows a similar setup. More specifically, the independent variables are replaced as $M\_Digital$ and $P\_Digital$, which refers to management digital transformation and production digital transformation. The regressions formulas are specified as follows:

For management digital transformation:

$$EDI_{it} = \beta_0 + \beta_1 M\_Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

$$ECI_{it} = \beta_0 + \beta_1 M\_Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

For production digital transformation:

$$EDI_{it} = \beta_0 + \beta_1 P\_Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

$$ECI_{it} = \beta_0 + \beta_1 P\_Digital_{it} + \boldsymbol{\beta} Control_{it} + \alpha_i + \gamma_t + \epsilon_{it}$$

The constant, control variables and the firm fixed effect, time fixed effects and error terms remained unchanged.

4.3.7. Descriptive statistics and Correlation Analysis.

This section provides a descriptive statistical analysis and correlation analysis of the sample used in the empirical study. The descriptive statistics in Table 13 show that Chinese listed firms engaged in export activities exhibit considerable variation in the number of export destinations, ranging from 0 to 182 countries and regions, with a standard deviation of 29.55. It is worth noting that some firms report zero export destinations in certain years, indicating that no exports occurred during those periods. However, this does not imply that these firms are not export-oriented; all firms in the sample have engaged in export activities at least once within the observed timeframe.

Regarding export concentration, the values range between 0 and 1, where a concentration of 0 indicates no exports in that year, and a concentration of 1 signifies that the firm exported exclusively to a single country. For cases where no exports were recorded, a value of 0 is assigned for export concentration, as it cannot be calculated without export activity. These statistics highlight the substantial variability in firms' export behaviours, suggesting that examining export performance alone is insufficient; the patterns of export behaviour themselves are of significant research interest.

Additionally, the descriptive statistics for management and production digital transformation reveal that the overall level of management digital transformation is higher than that of production digital transformation across the sample firms. This discrepancy underscores the differing degrees to which firms prioritize organizational and managerial improvements versus production efficiency enhancements in their digital transformation strategies. These differences offer valuable insights into how firms leverage digital transformation to support their internationalization efforts.

The correlation analysis in Table 14 reveals a strong negative correlation between export diversification and export concentration, indicating that firms with a wider range of export destinations tend to distribute their export resources more evenly across these markets. This could be due to firms attempting to maximize the benefits of having multiple export options while simultaneously mitigating the risks associated with reliance on fewer markets. However, it is important to note that the relationship between export diversification and export concentration is not strictly inverse. This suggests that an increase in the number of export destinations does not always result in a more dispersed export strategy. Some firms, paradoxically, exhibit both high export diversification and high export concentration, a phenomenon that warrants further investigation in future research.

Furthermore, the relationships among digital transformation, management digital transformation, and production digital transformation are also noteworthy. The correlation coefficients indicate a strong positive relationship between these three variables, suggesting that in practice, firms often pursue digital transformation in a comprehensive manner rather than focusing solely on one aspect. However, despite this high correlation, the analysis also uncovers inherent differences in the direction of digital transformation across firms, which are not uniform. Although these differences are subtle, the application of the LLM method discussed earlier allows for the identification of these nuanced distinctions.

Additionally, the correlation analysis provides a preliminary indication that management digital transformation enhances export diversification, while both management and production digital transformation appear to increase export concentration. This result contradicts our theoretical expectations. However, it is important to recognize that correlation analysis alone cannot accurately capture the relationships between these variables, particularly given the high degree of interrelationship between the two types of digital transformation. Therefore, in the following sections, we will employ more rigorous econometric methods to examine these relationships in greater depth.

Table 13. Descriptive statistics

Variable	N	Mean	p50	SD	Min	Max
EDI	9526	29.66	21	29.55	0	182
EHI	9526	0.377	0.271	0.294	0	1
Digital	9526	-0.274	-0.462	0.557	-0.578	6.422
DigitalM	9526	0	-0.282	1	-0.419	15.76
DigitalP	9526	0	-0.272	1	-0.320	18.56
LEV	9526	0.463	0.436	0.812	0.00800	63.97
ROA	9526	0.0410	0.0360	0.290	-14.59	20.79
ATO	9526	0.717	0.601	0.575	0.00200	11.84
Cashflow	9526	0.0390	0.0390	0.0800	-1.938	1.127
Growth	9526	0.727	0.110	22.30	-0.942	1878
Indep	9526	0.372	0.333	0.0560	0.182	0.800
BM	9526	0.930	0.604	1.040	0.00400	13.71
PB	9526	4.548	2.937	50.35	-2977	2789
Firmage	9526	2.729	2.773	0.379	0.693	3.912
SOE	9526	0.408	0	0.491	0	1
Top1	9526	0.355	0.337	0.151	0.0220	0.900
Liability	9526	0.00900	0.00100	0.0470	0	1.101
Cliability	9526	0.00700	0.00100	0.0330	0	0.800

Table 14. Correlation analysis

	EDI	*ECI*	*Digital*	*DigitalM*	*DigitalP*	*Lev*	*ROA*
EDI	1						
ECI	-0.603***	1					
Digital	0.032***	0.021**	1				
DigitalM	0.0140	0.031***	0.942***	1			
DigitalP	0.017*	0.025**	0.914***	0.926***	1		
Lev	0.018*	-0.00600	-0.0130	-0.017*	-0.0170	1	
ROA	0.00300	0.00500	0.00300	0.00700	0.00800	-0.513***	1
ATO	0.172***	-0.081***	-0.022**	-0.024**	-0.025**	0.026**	0.032***
Cashflow	0.062***	-0.053***	-0.00100	0.0110	0.00100	-0.075***	0.071***
Growth	-0.00700	0.00100	-0.00800	-0.00600	-0.00400	0.00900	0.00200
Indep	-0.00900	0.00600	0.034***	0.035***	0.029***	0.00700	-0.00100
BM	0.179***	-0.102***	-0.049***	-0.058***	-0.062***	0.118***	-0.045***
PB	-0.020*	0.022**	0.00100	0.00200	0.00100	0.00300	0.138***
Firmage	0.120***	-0.041***	0.048***	0.028***	0.0120	0.065***	-0.0140
SOE	0.128***	-0.073***	0.031***	0.00600	0.019*	0.069***	-0.026***
Top1	0.018*	-0.0120	-0.028***	-0.028***	-0.00700	-0.00200	0.0140
Liability	0.063***	-0.057***	-0.00100	-0.00500	-0.0150	0.046***	-0.00600
Cliability	0.082***	-0.066***	0.00300	-0.00200	-0.0130	0.050***	-0.00600

	ATO	*Cashflow*	*Growth*	*Indep*	*BM*	*PB*	*Firmage*
ATO	1						
Cashflow	0.081***	1					
Growth	0.0120	-0.018*	1				
Indep	-0.040***	-0.025**	-0.00500	1			
BM	0.078***	-0.087***	0.033***	0.052***	1		
PB	0.00400	-0.018*	0.000	0.0100	-0.036***	1	
Firmage	0.033***	0.022**	0.0160	-0.033***	0.064***	0.00500	1
SOE	0.103***	-0.021**	-0.0130	-0.037***	0.310***	-0.023**	0.197***
Top1	0.095***	0.079***	0.0140	0.052***	0.160***	-0.0120	-0.126***
Liability	0.043***	0.023**	0.095***	0.131***	0.399***	-0.0110	-0.044***
Cliability	0.059***	0.018*	0.092***	0.144***	0.418***	-0.0110	-0.049***

	SOE	*Top1*	*Liability*	*Cliability*
SOE	1			
Top1	0.207***	1		
Liability	0.155***	0.192***	1	
Cliability	0.157***	0.193***	0.982***	1

The correlation table is too large to be displayed in a single table, therefore Table 14 splits the whole table into 3 parts.

4.4. Results

4.4.1. Baseline Results

Based on the preceding analysis, we first employed empirical methods to examine the impact of digital transformation on firms' export diversity and export concentration. The results are presented in Table 15. It is important to note that, due to the substantial differences in scale between the explanatory and dependent variables in our empirical analysis, we centralized all variables before conducting the regression analysis. Similarly, all subsequent regressions in this study have undergone the same methodology process.

The RBV emphasizes that firm-specific resources and capabilities, which is valuable, rare, inimitable, and non-substitutable, are critical sources of competitive advantage. Within this framework, digital transformation provides the firms. Specifically, Columns 1 and 2 test the effect of digital transformation on export diversity and concentration in univariate regressions. Columns 3 and 4 examine the corresponding effects after including control variables. All regression models account for firm fixed effects and year fixed effects, and standard errors are clustered at the industry level to obtain robust standard errors.

Regarding export diversity, the regression coefficient of digital transformation is significant at the 0.01 level. Without control variables, an increase of one standard deviation in the level of digital transformation corresponds to an increase of 1.1897 standard deviations in export diversity. Even after adding control variables (as shown in Column 3), although the marginal effect is slightly reduced compared to Column 1, the positive effect remains statistically significant at the 0.01 level. Specifically, an increase of one standard deviation in digital transformation still leads to a 0.8926 standard deviation increase in export diversity. This finding aligns with our first hypothesis (H1a) that digital transformation significantly expands firms' access to international markets and increases export diversity.

However, concerning export concentration, digital transformation does not significantly affect export concentration, regardless of whether control variables are included (as seen in Columns 2 and 4). Although the relationship is not statistically significant in the full sample, the numerical results suggest a negative relationship, indicating that digital transformation may somewhat reduce export concentration by distributing exports more evenly across different countries. While this observation is consistent with our intuition and hypothesis H1b, it lacks statistical significance. Two possible explanations exist for this result. First, digital transformation may not influence a firm's preference for export destinations; thus, the proportion of exports to key countries remains unchanged, and there is no significant increase in the share of exports to countries that previously had a smaller export ratio. Second, it is possible that digital transformation can indeed affect firms' export preferences, but this effect is only evident in specific types of digital transformation. Based on this analysis, we will further differentiate between the two directions of digital transformation in the following sections to explore the underlying reasons for these results.

Table 15. Effect of Digital Transformation on Export Diversity and Export Concentration

	(1) *EDI*	(2) *ECI*	(3) *EDI*	(4) *ECI*
Digital	1.1897***	-0.0058	0.8926***	-0.0041
	(3.24)	(-1.44)	(3.01)	(-1.25)
Lev			0.0701	-0.0006
			(0.53)	(-1.51)
ROA			0.2439	-0.0066**
			(0.77)	(-2.75)
ATO			0.5432	-0.0061
			(1.29)	(-1.22)
Cashflow			1.7440*	-0.0043
			(2.01)	(-0.18)
Growth			0.0021	0.0000
			(0.47)	(0.10)
Indep			-4.9063	-0.0734**
			(-1.46)	(-2.24)
BM			0.4905**	-0.0025
			(2.69)	(-0.79)
PB			-0.0026***	0.0000***
			(-12.79)	(6.61)
Firmage			11.5591***	-0.0577***
			(6.88)	(-3.27)
SOE			1.0073	-0.0234*
			(1.40)	(-2.02)
Top1			1.4664	-0.0176
			(1.12)	(-0.50)
Liability			-42.6352	0.6672**
			(-0.86)	(2.31)
Cliability			50.5712	-0.8138*
			(0.67)	(-1.88)
Constant	30.2038***	0.3722***	-1.4296	0.5800***
	(361.43)	(399.27)	(-0.37)	(12.50)
Control	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.9479	0.7842	0.9485	0.7846
N	9526	9526	9526	9526

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4.2. A Further Discussion on Export Diversity.

Based on the results of the baseline regression, we observe the effects of digital transformation on firms' export diversification and export concentration. The empirical evidence suggests that while digital transformation has a significant impact on export diversification, it does not lead to notable changes in export concentration, which is the second key measure of export behaviour. In the preceding analysis, we discussed how digital transformation may take different forms across firms, leading to diverse outcomes. Specifically, as stated in Section 4.2.1, we categorized digital transformation into two types: production digital transformation, which focuses on enhancing production efficiency and reducing direct costs, and management digital transformation, which emphasises improving a firm's organizational and managerial capabilities. From the perspective of the Resource-Based View (RBV), production digital transformation strengthens a firm's production resources, while management digital transformation reorganizes existing resources to create unique, inimitable new capabilities.

Therefore, in this section and the subsequent section, discussions are built from this chapter's hypotheses to explore how different types of digital transformation significantly affect the firm's export behaviour. Export diversification and export concentration remain the primary indicators under consideration.

Regarding export diversification, the detailed results are presented in Table 16. From these results, it is evident that both production and management digital transformations significantly enhance a firm's export diversification.

Specifically, management digital transformation primarily enhances a firm's strategic, organizational, and managerial capabilities, enabling more effective internal coordination, improved market intelligence, and superior strategic decision-making processes. Such improvements foster stronger managerial competencies, which are often difficult for competitors to replicate due to their embeddedness in the organization's unique culture and management practices. Consequently, firms can better identify and exploit opportunities across a broader range of international markets, especially markets previously inaccessible due to managerial or informational constraints. The empirical evidence aligns with these theoretical predictions, as management digital transformation significantly increases export diversification. Specifically, after accounting for control variables, firm fixed effects, and year fixed effects, a one-standard-deviation increase in management digital transformation results in an average rise of 0.3855 standard deviations in the number of export destinations, equivalent to approximately 11 additional countries. This finding strongly supports hypothesis H2a, underscoring the critical role of managerial resources and capabilities as drivers of export market diversification.

On the other hand, production digital transformation strengthens firms' operational and technological resources, which enhance the overall efficiency and quality of production processes and lower production costs. According to RBV, such operational improvements constitute valuable and relatively tangible resources that firms can leverage broadly across multiple markets, thereby widening the potential market scope for their products. These improvements, however, are typically incremental and generalized, influencing the competitiveness of products across both existing and new potential markets without specific targeting. In other words, production digital transformation does not inherently prioritize one type of market over another; instead, it improves general market competitiveness. The empirical results confirm this theoretical expectation, showing that a one-standard-deviation increase in production digital transformation corresponds to a 0.3553 standard deviation increase in the number of export destinations, translating into approximately 10 additional countries. Although the effect magnitude is slightly smaller compared to management digital transformation, it remains significant and economically meaningful, thereby supporting hypothesis H2b.

Collectively, these findings illustrate how distinct types of digital transformation, viewed through the RBV lens, differently enhance a firm’s internal resource base and capabilities, subsequently influencing export diversification. Management digital transformation expands firms' strategic market reach by creating unique managerial competencies, whereas production digital transformation broadly enhances product marketability through improved operational efficiencies. The RBV provides a coherent theoretical underpinning to explain how these specific internal resource enhancements translate into observable changes in export behaviours, reinforcing the robustness and validity of our empirical results.

Table 16. Effect of Management and Production Digital Transformation on Export Diversification

	(1) *EDI*	(2) *EDI*	(3) *EDI*	(4) *EDI*
M_Digital	0.5020***		0.3855***	
	(3.28)		(3.34)	
P_Digital		0.4765***		0.3553**
		(3.13)		(2.79)
Lev			0.0711	0.0724
			(0.54)	(0.55)
ROA			0.2451	0.2481
			(0.78)	(0.79)
ATO			0.5462	0.5515
			(1.30)	(1.31)
Cashflow			1.7320*	1.7551*
			(1.99)	(2.02)
Growth			0.0021	0.0021
			(0.47)	(0.47)
Indep			-4.9201	-4.9853
			(-1.46)	(-1.48)
BM			0.4896**	0.4893**
			(2.69)	(2.69)
PB			-0.0026***	-0.0026***
			(-12.92)	(-12.87)
Firmage			11.6004***	11.6448***
			(6.76)	(6.79)
Soe			1.0287	1.0313
			(1.42)	(1.43)
Top1			1.4564	1.4152
			(1.12)	(1.08)
Liability			-42.8434	-43.1370
			(-0.86)	(-0.87)
Cliability			50.8183	51.1650
			(0.68)	(0.68)
Constant	29.8789***	29.8788***	-1.7874	-1.8757
	(869.27)	(871.31)	(-0.45)	(-0.47)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.9479	0.9479	0.9485	0.9485
N	9526	9526	9526	9526

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4.3. Heterogeneity on Export Concentration.

Turning now to export concentration, which measures the degree to which a firm's exports are concentrated in fewer or dispersed across more international markets, we continue applying the Resource-Based View (RBV) to interpret the empirical findings presented in Table 17. According to RBV, the type and nature of resources influence firms' strategic decisions on how to distribute their exports across different markets.

Management digital transformation, which enhances strategic managerial capabilities, significantly influences a firm's export concentration. Improved managerial resources facilitate superior communication, enhanced decision-making, and greater strategic flexibility. Firms with advanced management digital transformation capabilities are better equipped to identify and respond proactively to international market dynamics, balancing potential rewards against associated risks effectively. One significant risk firms seek to mitigate is overdependence on a limited number of markets, which increases vulnerability to market disruptions and fluctuations in exchange rates. Enhanced managerial capabilities enable firms to strategically diversify exports across a wider range of markets, effectively distributing risks and achieving a balanced export portfolio. Empirically, the results confirm this theoretical perspective: a one-standard-deviation increase in management digital transformation significantly decreases export concentration by 0.0031 standard deviations ($p < 0.01$), clearly supporting hypothesis H3a. This reduction demonstrates how advanced managerial capabilities empower firms to more effectively diversify exports, reduce reliance on key markets, and mitigate overall export risk.

In contrast, production digital transformation primarily improves firms' operational efficiency, product quality, and cost management. These operational resources broadly enhance competitiveness across all markets but lack specificity concerning strategic market distribution decisions. Improvements derived from production digital transformation are generalized in nature, simultaneously benefiting both established and potential new markets. Therefore, while production digital transformation can boost overall market competitiveness and facilitate entry into additional markets, it does not inherently influence firms' strategic allocation or redistribution of exports across specific markets. Empirical evidence supports this theoretical reasoning, as the impact of production digital transformation on export concentration is negative but statistically insignificant. This aligns with hypothesis H3b, indicating production-related improvements do not significantly alter export market distribution patterns.

Overall, the distinct resource-based mechanisms underlying management and production digital transformations lead to differentiated impacts on firms' export concentration. Management digital transformation, by enhancing strategic managerial resources, significantly reduces export concentration through improved export distribution and risk management. Production digital transformation, although valuable in enhancing general competitiveness, does not specifically influence strategic market allocation, thus demonstrating no significant effect on export concentration. By rigorously applying the Resource-Based View, this analysis provides clear theoretical justifications for the observed empirical outcomes.

Table 17. Effect of Management and Production Digital Transformation on Export Concentration

	(1) ECI	(2) ECI	(3) ECI	(4) ECI
M_Digital	-0.0037^{***}		-0.0031^{***}	
	(-2.90)		(-2.93)	
P_Digital		-0.0019		-0.0012
		(-0.81)		(-0.54)
Lev			-0.0006	-0.0006
			(-1.50)	(-1.53)
ROA			-0.0066^{**}	-0.0067^{**}
			(-2.75)	(-2.80)
ATO			-0.0060	-0.0061
			(-1.22)	(-1.21)
Cashflow			-0.0042	-0.0044
			(-0.18)	(-0.18)
Growth			0.0000	0.0000
			(0.10)	(0.09)
Indep			-0.0735^{**}	-0.0731^{**}
			(-2.24)	(-2.23)
BM			-0.0025	-0.0025
			(-0.79)	(-0.79)
PB			0.0000^{***}	0.0000^{***}
			(6.66)	(6.65)
Firmage			-0.0573^{***}	-0.0583^{***}
			(-3.23)	(-3.25)
Soe			-0.0236^{*}	-0.0235^{*}
			(-2.03)	(-2.02)
Top1			-0.0178	-0.0174
			(-0.51)	(-0.50)
Liability			0.6654^{**}	0.6701^{**}
			(2.30)	(2.30)
Cliability			-0.8125^{*}	-0.8170^{*}
			(-1.88)	(-1.88)
Constant	0.3738^{***}	0.3738^{***}	0.5800^{***}	0.5825^{***}
	(969.64)	(973.48)	(12.51)	(12.35)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.7842	0.7842	0.7846	0.7846
N	9526	9526	9526	9526

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5. Robustness Tests

In our analysis, we have carefully selected explanatory and dependent variables that serve as reasonable proxies for testing our hypotheses. Additionally, we have included control variables to account for potential causal relationships between the explanatory and dependent variables. To further minimise potential biases arising from endogeneity issues and variable selection bias, we conducted a series of robustness checks. Specifically, we first mitigate the impact of endogeneity on our empirical results by employing generalized method of moments (GMM) estimation techniques. Second, we redefined the proxies for the dependent variables, Export Diversification Index (EDI) and Export Concentration Index (ECI), and then performed regression analyses again. Lastly, we revised the measurement of the independent variables, particularly those representing production digital transformation and management digital transformation, and then re-evaluated the baseline regressions.

4.5.1. Robustness Check Using GMM Estimation

This study investigates the effects of different types of digital transformation on firms' export behaviour using a high-dimensional fixed effects model. However, as noted in the literature (F. Wang & Ye, 2023; Y. Wang et al., 2024), digital transformation is an endogenous firm-level decision, and despite the use of fixed effects and control variables to mitigate such concerns, endogeneity issues remain, particularly for production and management digital transformations. The Generalized Method of Moments (GMM) estimation, which uses lagged explanatory variables as instruments, helps mitigate endogeneity concerns to some extent. Therefore, in the robustness checks, we re-estimated the impact of general digital transformation, as well as its subcategories (production and management digital transformation), on firms' export behaviour using the GMM model.

In our estimation context, considering the potential reverse causality and endogeneity issues between different types of digital transformation and firms' export behaviour, we adopt the two-step difference GMM estimator proposed by Arellano and Bond (Arellano & Bond, 1991). This estimation could effectively mitigate biases caused by unobserved firm-level heterogeneity, omitted variables, and reverse causality through internal instruments constructed from lagged values of the endogenous explanatory variables.

In our empirical model, both production digital transformation and management digital transformation are treated as endogenous variables. To explicitly address endogeneity, we use the lagged values of the management digital transformation variable (specifically, the third and fourth lags) as internal instruments. Moreover, to avoid the proliferation of instruments, which can weaken estimation validity, these instruments are collapsed following standard practices recommended in recent econometric literature。The results of these tests are presented in Table 18 and Table 19.

Table 18. GMM estimation results (EDI)

	(1) *EDI*	(2) *EDI*	(3) *EDI*
Digital	7.657^{***}		
	(2.552)		
M_Digital		1.389^{**}	
		(0.631)	
P_Digital			1.020^{*}
			(0.635)
Lev	0.051	0.049	0.046
	(0.042)	(0.043)	(0.042)
ROA	0.188	0.176	0.165
	(0.130)	(0.137)	(0.140)
ATO	0.506	0.460	0.434
	(0.360)	(0.337)	(0.329)
Cashflow	1.176	1.126	1.086
	(1.109)	(1.115)	(1.115)
Growth	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
Indep	-4.212	-4.054	-4.237^{*}
	(2.741)	(2.655)	(2.633)
BM	0.620^{***}	0.579^{***}	0.573^{***}
	(0.153)	(0.145)	(0.144)
PB	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
Firmage	-0.484	4.949^{***}	5.928^{***}
	(2.476)	(1.321)	(1.156)
Soe	-0.015	0.063	0.058
	(0.869)	(0.842)	(0.833)
Top1	1.940	1.040	0.580
	(2.235)	(2.139)	(2.125)
Liability	-13.775	-17.335	-18.299
	(15.960)	(14.952)	(14.762)
Cliability	8.779	13.608	15.161
	(24.943)	(24.099)	(23.950)
Robust	Yes	Yes	Yes
Twostep	Yes	Yes	Yes
Noleveleq	Yes	Yes	Yes
N	7237	7237	7237

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19. GMM estimation results (ECI)

	(1) ECI	(2) ECI	(3) ECI
Digital	-0.145**		
	(0.064)		
M_Digital		-0.032**	
		(0.016)	
P_Digital			-0.027
			(0.017)
Lev	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
ROA	-0.003	-0.003	-0.003
	(0.004)	(0.004)	(0.004)
ATO	-0.006	-0.005	-0.005
	(0.008)	(0.008)	(0.008)
Cashflow	-0.024	-0.024	-0.024
	(0.025)	(0.024)	(0.024)
Growth	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Indep	-0.046	-0.046	-0.040
	(0.050)	(0.049)	(0.049)
BM	-0.004	-0.003	-0.003
	(0.004)	(0.004)	(0.004)
PB	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Firmage	0.069	-0.021	-0.041
	(0.060)	(0.031)	(0.026)
Soe	-0.020	-0.021	-0.021
	(0.022)	(0.022)	(0.022)
Top1	-0.001	0.009	0.014
	(0.050)	(0.049)	(0.049)
Liability	0.557	0.581	0.597
	(0.423)	(0.423)	(0.421)
Cliability	-0.507	-0.525	-0.545
	(0.556)	(0.555)	(0.552)
Robust	Yes	Yes	Yes
Twostep	Yes	Yes	Yes
Noleveleq	Yes	Yes	Yes
N	7237	7237	7237

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regarding the results and diagnostic tests of the GMM regression, using the estimation of the effect of management digital transformation on firms' export diversification as an example, the results indicate a positive and statistically significant relationship between management digital transformation and export diversification (EDI). Specifically, the estimated coefficient for management DT is 1.389 ($p = 0.028$), suggesting that an increase in management-related digital transformation significantly enhances a firm's ability to diversify its export markets. Among control variables, only the book-to-market ratio (bm, coefficient = 0.579, $p < 0.001$) and firm age (firmage, coefficient = 4.949, $p < 0.001$) show significant impacts on export diversification. Other control variables such as leverage, return on assets, cash flow, and governance variables do not display significant effects.

With respect to the diagnostic tests, the Arellano-Bond autocorrelation tests first show that the first-order autocorrelation test (AR(1), $z = -4.87$, $p < 0.001$) confirms significant first-order serial correlation in the differenced residuals, which is consistent with the expectations based on the construction of the GMM estimator. Critically, the absence of significant second-order autocorrelation (AR(2), $z = -1.83$, $p = 0.067$) supports the validity of using lagged values as instruments, a key assumption underpinning difference GMM. Subsequently, in the instrument validity tests, the Sargan test (chi-square = 0.47, $p = 0.492$) and the robust Hansen test (chi-square = 1.69, $p = 0.193$) both fail to reject the null hypothesis, indicating no significant over-identification problem. These results indicate that the internal instruments employed (lagged values of management DT) are adequately valid and not correlated with the error terms, further supporting the credibility of our estimation.

Similarly, Tables 18 and 19 present the main results of the other regressions. Specifically, Table 18 shows the effects of general digital transformation, production digital transformation, and management digital transformation on firms’ export diversity. The results indicate that all forms of digital transformation—whether general or specific to production or management—have a significant positive impact on export diversity, consistent with the baseline regression results. This confirms the robustness of our empirical findings concerning export diversity.

Table 19, in turn, presents the results for export concentration. Both general digital transformation and management digital transformation significantly reduce export concentration, aligning with the findings from the baseline regression. However, the results show that production digital transformation does not have a significant impact on export concentration. This suggests that production digital transformation does not play a substantial role in distributing a firm's exports more evenly across markets, indicating that this mechanism is not clearly identifiable in our analysis. These results further confirm the robustness of the main findings in the paper.

In summary, the GMM results robustly demonstrate that management digital transformation significantly contributes to the diversification of export markets, after carefully addressing potential endogeneity issues. The diagnostic tests confirm the appropriateness of our econometric approach, reinforcing the reliability of our findings.

4.5.2. Alternative Measurement of Export Diversity and Concentration

In our baseline regression, the dependent variable, export diversification index (EDI), is measured by the number of countries to which a firm exports. While the number of export destinations provides an intuitive and straightforward measure of export diversity, it primarily captures the firm's current export behaviour, making it a static indicator. However, a substantial body of literature emphasises the importance of understanding firms' entry and exit behaviours in foreign markets, which focus on dynamic changes in a firm's market presence rather than static measures. These dynamic indicators better capture the actual impact of digital transformation on a firm's export behaviour. Therefore, building on the discussion of both measurement approaches and the baseline regression, we use a dynamic measure as an alternative indicator of a firm's export diversity. Specifically, we group the data by firm and sort it by year to calculate the percentage change in the number of export destinations year-over-year. A positive value indicates an increase in the number of export destinations compared to the previous year, while a negative value indicates a decrease. This dynamic indicator allows us to validate the robustness of our baseline empirical analysis and provides a valuable complement to the static indicator.

Regarding the Export Concentration Index (ECI), our baseline regression uses the Herfindahl Index, which is calculated as the sum of the squared proportions of each country's share of a firm's total exports. However, there is debate in the academic literature about how to best define export shares. Some studies argue that export values, as measured by monetary value, are the most direct measure of a firm's export performance, making the use of export values the most accurate way to represent a firm's export distribution across countries. Other scholars, however, suggest that because different firms export various products, using export value to summarize export behaviour may not fully capture the reality. Instead, they advocate for using export quantities, which might more accurately reflect the firm's true export activities by considering the volume of goods. Each of these perspectives has its merits and drawbacks. In our baseline regression, we used export value as the measure; however, in our robustness checks, we employed the concentration of export quantities as an alternative measure.

In summary, for robustness testing of the dependent variables, we use the percentage change in the number of export destinations to replace the absolute number of export destinations for export diversity (EDI). For export concentration (ECI), we substitute the concentration of export value with the concentration of export quantity. The regression results are presented in Table 20.

The results in Table 20 indicate that when using alternative measures for ECI and EDI, digital transformation has a significant positive impact on a firm's export diversity, while there is no statistically significant effect on export concentration. These findings are consistent with those from our baseline regression. Furthermore, Tables 21 and 22 show that when examining the effects of production digital transformation and management digital transformation on the alternative EDI and ECI measures separately, both types of digital transformation significantly increase export diversity. However, only management digital transformation significantly reduces export concentration, whereas production digital transformation has no statistically significant impact on export concentration. These results align with the empirical findings presented earlier in the study, demonstrating the robustness of the findings despite using different approaches to construct the dependent variables.

Table 20. Effect of digital transformation on export behaviour

(Alternative Dependent variable)

	(1) *EDI_Alt*	(2) *ECI_Alt*	(3) *EDI_Alt*	(4) *ECI_Alt*
Digital	0.0680^{***}	-0.0079	0.0830^{***}	-0.0036
	(5.14)	(-0.55)	(5.28)	(-0.23)
Lev			-0.0059	0.0024^{***}
			(-0.82)	(4.22)
ROA			0.0076	0.0078^{***}
			(0.32)	(3.52)
ATO			0.0390^{***}	-0.0139^{**}
			(3.12)	(-2.85)
Cashflow			0.0549	0.0443^{**}
			(0.57)	(2.41)
Growth			-0.0004	-0.0000
			(-1.20)	(-0.45)
Indep			0.1237	0.0414
			(0.40)	(1.65)
BM			-0.0524^{*}	-0.0057
			(-1.89)	(-0.99)
PB			-0.0002^{***}	0.0000^{***}
			(-4.58)	(4.47)
Firmage			-0.5034^{***}	-0.1483^{***}
			(-4.02)	(-4.64)
SOE			-0.0441	0.0042
			(-0.86)	(0.52)
Top1			0.4734^{**}	0.0348^{*}
			(2.42)	(1.82)
Liability			1.5016	0.6952^{**}
			(0.95)	(2.62)
Cliability			-1.0768	-0.7384^{*}
			(-0.48)	(-1.83)
Constant	0.2353^{***}	0.3444^{***}	1.4331^{***}	0.7315^{***}
	(53.27)	(89.88)	(3.54)	(8.22)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.1817	0.7464	0.1826	0.7475
N	9524	9526	9524	9526

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21. Effect of Management and Production DT on Export Diversification (Alternative dependent variable)

	(1)	(2)	(3)	(4)
	EDI_Alt	*EDI_Alt*	*EDI_Alt*	*EDI_Alt*
M_Digital	0.0242^{***}		0.0300^{***}	
	(5.22)		(5.60)	
P_Digital		0.0468^{***}		0.0528^{***}
		(6.24)		(6.08)
Lev			-0.0057	-0.0058
			(-0.80)	(-0.81)
ROA			0.0078	0.0076
			(0.33)	(0.33)
ATO			0.0395^{***}	0.0390^{***}
			(3.17)	(3.14)
Cashflow			0.0540	0.0565
			(0.57)	(0.59)
Growth			-0.0004	-0.0004
			(-1.19)	(-1.19)
Indep			0.1218	0.1151
			(0.39)	(0.37)
BM			-0.0525^{*}	-0.0526^{*}
			(-1.89)	(-1.89)
PB			-0.0002^{***}	-0.0002^{***}
			(-4.54)	(-4.54)
Firmage			-0.4967^{***}	-0.5031^{***}
			(-3.96)	(-4.01)
Soe			-0.0425	-0.0402
			(-0.83)	(-0.78)
Top1			0.4715^{**}	0.4701^{**}
			(2.42)	(2.42)
Liability			1.4701	1.4825
			(0.93)	(0.93)
Cliability			-1.0426	-1.0426
			(-0.47)	(-0.46)
Constant	0.2167^{***}	0.2167^{***}	1.3927^{***}	1.4126^{***}
	(63.05)	(62.88)	(3.43)	(3.46)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.1817	0.1818	0.1826	0.1827
N	9524	9524	9524	9524

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22. Effect of Management and Production DT on Export Concentration (Alternative dependent variable)

	(1)	(2)	(3)	(4)
	ECI_Alt	*ECI_Alt*	*ECI_Alt*	*ECI_Alt*
M_Digital	-0.0061		-0.0138^{**}	
	(-0.91)		(-2.80)	
P_Digital		-0.0022		-0.0003
		(-0.29)		(-0.03)
Lev			0.0024^{***}	0.0024^{***}
			(4.30)	(4.16)
ROA			0.0079^{***}	0.0078^{***}
			(3.54)	(3.54)
ATO			-0.0044	-0.0140^{**}
			(-0.60)	(-2.89)
Cashflow			0.0444^{**}	0.0443^{**}
			(2.41)	(2.42)
Growth			-0.0000	-0.0000
			(-0.45)	(-0.45)
Indep			0.0412	0.0416
			(1.64)	(1.66)
BM			-0.0057	-0.0057
			(-0.98)	(-0.98)
PB			0.0000^{***}	0.0000^{***}
			(4.46)	(4.40)
Firmage			-0.1471^{***}	-0.1491^{***}
			(-4.63)	(-4.70)
Soe			0.0039	0.0042
			(0.46)	(0.50)
Top1			0.0343^{*}	0.0351^{*}
			(1.80)	(1.81)
Liability			0.6902^{**}	0.6989^{**}
			(2.61)	(2.64)
Cliability			-0.7340^{*}	-0.7421^{*}
			(-1.81)	(-1.84)
Constant	0.3466^{***}	0.3466^{***}	0.7295^{***}	0.7346^{***}
	(746.85)	(755.47)	(8.48)	(8.50)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.7464	0.7464	0.7475	0.7475
N	9526	9526	9526	9526

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5.3. Alternative Classify Method of Digital Transformation

In our baseline regression, we used a large language model (LLM) to classify firms' digital transformation into two categories: production digital transformation and management digital transformation, based on the specific transformation logic indicated by the keywords. However, during the classification process, some keywords were too broad to be directly assigned to a single category. For instance, terms like "Digital Transformation" or "Artificial Intelligence" encompass technologies and strategies that could be relevant to both enhancing production efficiency in the context of production digital transformation and improving management effectiveness for management digital transformation. In the baseline regression, these ambiguous keywords were assigned equally to both categories. However, because these keywords do not accurately reflect a firm's specific direction of digital transformation in certain contexts, we refined our approach during the robustness checks. We excluded these broad keywords and retained only those that could be clearly categorized into either production or management digital transformation. We then constructed corresponding alternative indicators and conducted robustness checks. The results of these tests are presented in Table 23 and Table 24.

The regression results indicate that when applying a more stringent classification standard for production and management digital transformation, the empirical findings remain largely consistent with those of the baseline regression. Specifically, for the Export Diversification Index (EDI), both production digital transformation and management digital transformation, as measured by the alternative method, have a significant positive impact. This suggests that both types of digital transformation effectively help firms expand their presence in international markets, consistent with the main findings of our analysis. Regarding the Export Concentration Index (ECI), management digital transformation significantly reduces export concentration, aligning with the results from our main analysis. Production digital transformation also significantly decreases export concentration; however, it shows lower statistical significance compared to management digital transformation. Moreover, the effect size of production digital transformation is 30% smaller than that of management digital transformation, indicating that management digital transformation remains the primary mechanism for reducing export concentration. These findings are consistent with our main analysis and further confirm the robustness of our empirical results.

Table 23. Effect of Management and Production DT on Export Diversification (Alternative independent variable)

	(1)	(2)	(3)	(4)
	EDI	*EDI*	*EDI*	*EDI*
M_Digital_Alt	0.3412^{**}		0.2713^{***}	
	(2.81)		(3.09)	
P_Digital_Alt		0.1856^{***}		0.1635^{***}
		(3.28)		(3.17)
Lev			0.0721	0.0743
			(0.55)	(0.56)
ROA			0.2465	0.2519
			(0.79)	(0.80)
ATO			0.5523	0.5710
			(1.31)	(1.35)
Cashflow			1.7165^{*}	1.7884^{*}
			(1.99)	(2.08)
Growth			0.0021	0.0022
			(0.48)	(0.48)
Indep			-4.8561	-4.9213
			(-1.44)	(-1.46)
BM			0.4907^{**}	0.4890^{**}
			(2.69)	(2.69)
PB			-0.0026^{***}	-0.0025^{***}
			(-12.98)	(-12.87)
Firmage			11.6600^{***}	11.7395^{***}
			(6.71)	(6.76)
Soe			1.0057	0.9953
			(1.39)	(1.37)
Top1			1.4797	1.4890
			(1.13)	(1.13)
Liability			-42.9654	-43.4592
			(-0.87)	(-0.87)
Cliability			50.8068	51.2376
			(0.67)	(0.68)
Constant	29.8787^{***}	29.8787^{***}	-1.9769	-2.1830
	(869.95)	(878.18)	(-0.49)	(-0.54)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.9479	0.9479	0.9485	0.9485
N	9526	9526	9526	9526

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24. Effect of Management and Production DT on Export Concentration (Alternative independent variable)

	(1) ECI	(2) ECI	(3) ECI	(4) ECI
M_Digital_Alt	-0.0038***		-0.0035**	
	(-3.15)		(-2.80)	
P_Digital_Alt		-0.0026**		-0.0025**
		(-2.58)		(-2.51)
Lev			-0.0006	-0.0006
			(-1.50)	(-1.54)
ROA			-0.0066**	-0.0067**
			(-2.73)	(-2.79)
ATO			-0.0060	-0.0063
			(-1.23)	(-1.27)
Cashflow			-0.0040	-0.0050
			(-0.16)	(-0.20)
Growth			0.0000	0.0000
			(0.10)	(0.09)
Indep			-0.0745**	-0.0738**
			(-2.30)	(-2.23)
BM			-0.0025	-0.0024
			(-0.79)	(-0.78)
PB			0.0000***	0.0000***
			(6.65)	(6.66)
Firmage			-0.0572***	-0.0581***
			(-3.25)	(-3.23)
Soe			-0.0234*	-0.0233*
			(-2.01)	(-2.01)
Top1			-0.0184	-0.0188
			(-0.52)	(-0.55)
Liability			0.6632**	0.6691**
			(2.31)	(2.31)
Cliability			-0.8089*	-0.8136*
			(-1.87)	(-1.88)
Constant	0.3738***	0.3738***	0.5803***	0.5827***
	(973.30)	(978.59)	(12.62)	(12.43)
Control	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Adjusted R^2	0.7842	0.7842	0.7846	0.7846
N	9526	9526	9526	9526

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6. Discussion and Conclusions

In the conclusion of this study, we revisited the impact of digital transformation on firms' export behaviour, particularly focusing on the relationship between export diversification and export concentration. Based on empirical research on Chinese listed companies, we demonstrated that digital transformation, particularly in the realms of management and production, significantly affects firms' export behaviours. The core contributions of this paper can be summarized into three key points:

First, this paper differentiates between management digital transformation and production digital transformation, analysing their respective impacts on firms' export diversification. From the perspective of the Resource-Based View (RBV), management digital transformation represents the optimization and reorganization of a firm's internal resources. By enhancing information processing, market forecasting, and supply chain management capabilities, firms can more effectively enter new international markets. The empirical results support this view, showing that management digital transformation significantly increases the number of export destinations. In other words, management digital transformation enables firms to better identify and seize international market opportunities, reducing the risks associated with entering new markets and ultimately improving export diversification. Production digital transformation similarly has a positive impact on export diversification. By improving production efficiency, product quality, and operational flexibility, production digital transformation enables firms to respond swiftly to the diverse demands of global markets, thereby expanding their international market reach. The analysis results confirm Hypotheses H2a and H2b, showing that both management and production digital transformations contribute to increasing a firm's export diversification.

Second, this paper reveals the differing impacts of digital transformation on export concentration, highlighting the crucial role of management digital transformation in reducing export concentration. The results show that management digital transformation significantly lowers export concentration. This means that by implementing management digital transformation, firms can optimize their export resource allocation, distributing their exports more evenly across multiple markets rather than relying heavily on just a few. The application of big data analytics, cloud computing, and artificial intelligence enables firms to more effectively manage cross-border supply chains and allocate resources, thereby reducing export concentration. This finding aligns with Hypothesis H3a, demonstrating that management digital transformation helps firms mitigate market risk by reducing dependency on single markets. In contrast, the influence of production digital transformation on export concentration is less pronounced. The results indicate that production digital transformation does not significantly alter the firm's market distribution strategy. This may be because production digital transformation primarily focuses on improving efficiency and product quality, rather than directly influencing the structure of market distribution. These findings confirm Hypothesis H3b, suggesting that production digital transformation, in some cases, might even increase reliance on existing markets, particularly those of strategic importance.

Third, the findings of this paper have important practical implications for policymakers and corporate managers, particularly in the current context of global digital transformation. This research not only provides theoretical support for understanding how digital transformation influences firms' internationalization behaviours but also offers practical insights for firms in formulating digital strategies. As digital transformation accelerates on a global scale, it becomes increasingly crucial for firms to understand its role in shaping export behaviours. The results indicate that management and production digital transformations play distinct roles in firms' international expansion, and firms should flexibly choose the appropriate digital transformation path based on their resources and market strategies. For policymakers, the findings underscore the importance of promoting digital transformation, especially management digital transformation, to help firms enhance their competitiveness in global markets.

Inevitably, this study contains several areas in need of further refinement. First, the categorization of digital transformation remains simple. In this research, digital transformation is classified only into production digital transformation and management digital transformation for empirical analysis. In practice, however, digital transformation can involve numerous motivations and directions, and examining these more closely would enhance the practical value of the findings. From a data perspective, the text analysis method employed here relies on a relatively limited number of keywords extracted from annual reports of listed firms, which may compromise the precision of variable estimation. With the advancement of more precise and efficient text analysis technologies in the future, additional keywords could be incorporated to address current limitations in the textual data.

Future research can further explore the impact of digital transformation on export behaviours across different industries and regions, especially in uncertain and volatile market environments. Additionally, as digital technologies continue to evolve rapidly, the content and form of digital transformation are constantly changing. How to capture these changes and study their long-term impact on firms' internationalization remains a valuable research direction.

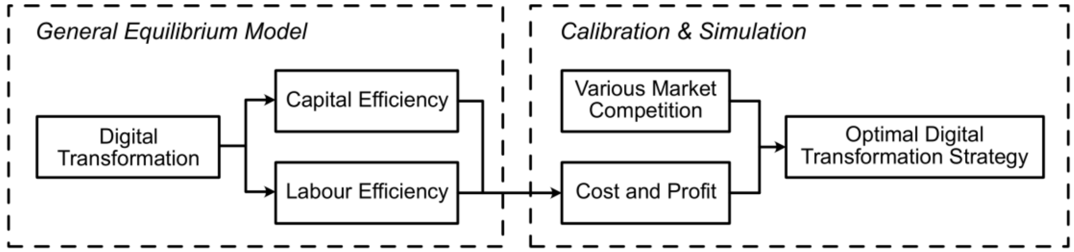
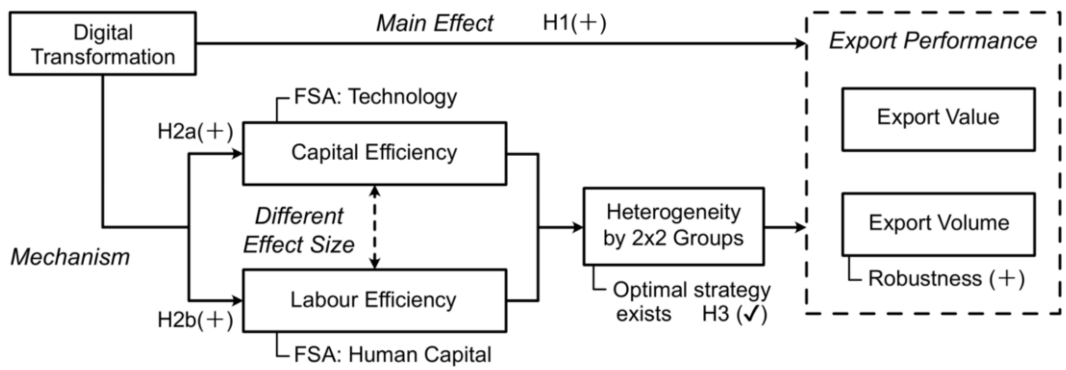
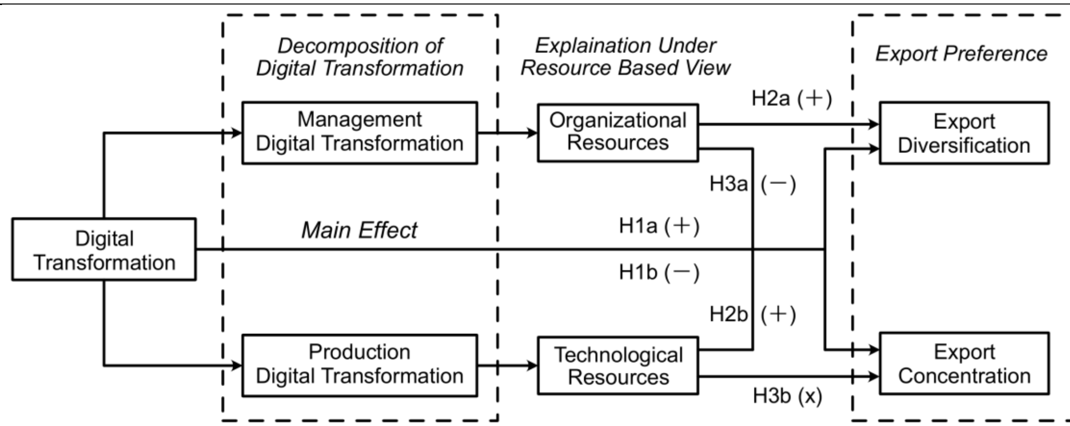
Chapter 5: Conclusions

This chapter provides a comprehensive summary of the leading research findings of this PhD thesis and discusses the academic contributions and practical implications of each study. It also addresses the limitations of the research and proposes potential directions for future exploration.

5.1. Summary of Main Research Findings

Digital transformation has become a popular topic in recent years, and its impact on enterprises has been extensively examined (Feliciano-Cestero et al., 2023; Hanelt et al., 2021; Vial, 2019). However, within the field of international business, discussions on how digital transformation influences firms' export activities are relatively limited (Bharadwaj et al., 2013). Existing studies are not only few in number but also often rely on simple empirical correlations, lacking theoretical depth (Acemoglu & Restrepo, 2018b, 2018a; C. S. A. Cheng et al., 2020; Filatotchev et al., 2009; Melitz & Redding, 2021). Particularly at the micro level, there is a scarcity of research exploring the mechanisms by which digital transformation affects firms' production efficiency, costs, and profits (Hanelt et al., 2021). At the meso-level of empirical research, the accurate measurement of digital transformation remains a significant challenge (Abeliansky & Hilbert, 2017; Denicolai et al., 2021; George et al., 2021). Further, there is a lack of in-depth analysis on how digital transformation impacts firms' capital and labour efficiencies, and subsequently, their export performance (Ghasemaghaei et al., 2017; K. Kim, 2018). Regarding firm's export behaviours, questions regarding a more detailed definition of the directions of digital transformation and how these varying directions affect firms' export behaviours are yet to be thoroughly investigated. Addressing these gaps, this doctoral thesis operates within the overarching framework of digital transformation and firms' exports to fill the aforementioned research gap in the literature. The theoretical perspectives, research hypotheses, empirical methods, and key findings of the three main studies are elaborated in Table 25.

Table 25. Summary of the three research

Research Focus	Theoretical Framework	Results
Chapter 2: A theoretical model on the mechanisms by which digital transformation affects firms' exports.		General equilibrium model: ✓ Calibration: ✓ Simulation: ✓ Optimal transformation strategy condition on market competition: ✓
Chapter 3: The empirical research on the effects of digital transformation on firm export performance		**Sample size:** 9682 **Method:** High dimensional fixed effects model. **Hypotheses:** H1: ✓ H2a & H2b: ✓ H3: ✓ **Robust test:** Yes
Chapter 4: The relationship between directions of digital transformation directions and export behaviours of firms.		**Sample size:** 9526 **Method:** High dimensional fixed effects model. **Hypotheses:** H1a & H1b: ✓ H2a & H2b: ✓ H3a & H3b: ✓ **Robust test:** Yes

As summarized in Table 25, Chapter 2 presents a theoretical model addressing the first research question posed in the introduction: *What is the theoretical model that describes the mechanism of how digital transformation affects firms' exports?* To thoroughly explore the internal mechanisms, this chapter employs a general equilibrium model as a starting point, conceptualizing digital transformation as an endogenous decision made by firms (Krugman, 1979, 1980; Melitz, 2003). This decision independently impacts both capital efficiency and labour efficiency. According to production theory, the effects of digital transformation on these efficiencies subsequently influence firms' fixed and variable costs. Therefore, in equilibrium, the degree of a firm's digital transformation and the level of market competition it faces become critical factors determining its profitability and even its ability to survive. The equilibrium model reveals that digital transformation is not without drawbacks; factors such as production costs, the costs of implementing digital transformation, and the intensity of market competition must be carefully considered to achieve profit maximization. The subsequent parameter calibration and simulation in this chapter further corroborate this viewpoint. Moreover, during the simulation phase, the study provides a detailed analysis of the firm's optimal degree of digital transformation across market environments ranging from low to extremely high competition. The simulation results demonstrate that blindly promoting digital transformation may reduce a firm's profits and even threaten its survival, which aligns with minority views in the existing literature (Feliciano-Cestero et al., 2023; Vial, 2019; Weill & Woerner, 2018). Furthermore, the firm's optimal degree of digital transformation is related to the intensity of market competition it faces. For example, in monopolistic markets, not implementing digital transformation is the optimal strategy, while in highly competitive markets, either not implementing it or fully embracing digital transformation is preferable to adopting it to a moderate degree. In summary, the implementation of digital transformation requires firms to carefully weigh their options and make optimal decisions based on cost structures and market environments.

Unlike the theoretical analysis and mathematical modelling presented in Chapter 2, Chapter 3 tries to answer the second research question: *How can the degree of digital transformation be measured accurately, and what empirical evidence links this measurement to firms' export performance?* This chapter provides an empirical examination of how digital transformation affects firms' export performance and the underlying mechanisms. In the field of international business, export performance is a crucial indicator of a firm's profitability and market competitiveness (Banalieva & Dhanaraj, 2019; Bernard et al., 2007; Verbeke & Yuan, 2024). According to the Firm-Specific Advantage (FSA) theory, a firm's unique advantages enable it to enhance the competitiveness of its products in international markets, thereby improving export performance (Aharoni, 1993; Kedia et al., 2012; Le & Lei, 2018). However, these advantages evolve over time and can vary significantly across different market environments and historical contexts (Banalieva & Dhanaraj, 2019; Chiao et al., 2006; Feliciano-Cestero et al., 2023). In the digital economy era, firms' FSAs have shifted from traditional factors such as company size and number of employees to dimensions like technology and human capital (Calderon-Monge & Ribeiro-Soriano, 2023; Verhoef et al., 2021; Wessel et al., 2021). Strengths in these two areas directly influence the magnitude of a firm's FSAs and, consequently, its export performance (Cuervo-Cazurra et al., 2018; Hennart et al., 2017; Sun & Lee, 2019). As demonstrated in the theoretical model of Chapter 2, digital transformation can significantly enhance firms' capital efficiency and labour efficiency, aligning with the two critical FSAs required in the digital age (Adarkwah & Malonæs, 2022). Therefore, this study hypothesizes that digital transformation improves firms' export performance by boosting their capital and labour efficiencies. From a theoretical perspective, this chapter discussed the differences between capital and labour efficiencies, proposing that they influence firms through distinct mechanisms and with varying effect sizes. Furthermore, the study explores the optimal degree of digital transformation under different combinations of firms' efficiencies. For the empirical analysis, China was selected due to its status as one of the world's largest exporters and one of the most digitally advanced economies. The research sample consists of 9,682 observations from listed Chinese companies between 2010 and 2016. Regarding methodology and results, text analysis on annual review of the firms, high-dimensional fixed effects models, subgroup regressions, and a series of robustness tests all support the research hypotheses (Guimarães & Portugal, 2010; Wooldridge, 2001). These findings not only confirm the positive impact of digital transformation on firms' export performance but also demonstrate the differences between the two mechanisms and validate the existence of an optimal digital transformation strategy.

Chapter 4 adopts a different perspective by exploring how various directions of digital transformation influence firms' export preferences and answers the last research question in the introduction part: *How do different directions of digital transformation shape firms' export behaviours?* Initially, this section addresses the drawbacks of employing a singular measurement for digital transformation and decomposes it into two distinct categories (Gong & Ribiere, 2021; Markus & Rowe, 2021): production digital transformation and management digital transformation, utilizing Large Language Models (LLMs) for differentiated measurement (M. Liu & Shi, 2024). Subsequently, it interprets these two types of digital transformation through the lens of the Resource-Based View (RBV) theory, associating management digital transformation with organizational resources and production digital transformation with technological resources (Barney, 1991, 2001; Elia et al., 2021). Regarding exports, firms' export preferences are reflected in their export behaviours, specifically manifested in their entry into and exit from international markets, as well as the distribution of their exports across different markets (Fabling & Sanderson, 2013; Haddoud et al., 2021). From a micro-level perspective, a firm's entry into more markets indicates stronger market competitiveness, while the distribution of exports abroad demonstrates its ability to effectively allocate export portfolios and mitigate risks, highlighting the importance of export behaviour (Ashaari et al., 2021; Jadhav et al., 2023). Empirically, based on literature concerning firms' export behaviours, this section proposes using export diversification and export concentration as two indicators to measure export behaviour. It further posits that the two types of digital transformation have heterogeneous impacts on firms' export diversification and export concentration. The empirical analysis employs a sample of 9,526 listed Chinese firms, utilizing high-dimensional fixed effects models and a series of robustness tests to support the three proposed research hypotheses. The results indicate that management digital transformation can simultaneously enhance firms' export diversification and reduce export concentration, whereas production digital transformation has a significant positive effect only on export diversification. This outcome suggests that different directions of digital transformation indeed exert heterogeneous effects on firms' export behaviours. Selecting the appropriate digital transformation direction can significantly assist firms in expanding their export options in international markets and managing their export strategies more effectively.

In summary, the main findings across the three chapters systematically elucidate the analysis of digital transformation's internal operational mechanisms, the validation of its impact on external export performance, and the examination of firms' export preferences. These aspects comprehensively discuss the influence of digital transformation on exporting firms from three dimensions. The studies provide multiple pieces of evidence at both the theoretical and empirical levels, aiding firms in optimizing the degree and direction of their digital transformation based on their specific conditions and environmental contexts.

5.2. Research Contribution

The three studies presented in Chapters 2, 3, and 4 integrate theoretical analysis, mathematical modelling, and empirical testing, resulting in the main contributions summarized in Table 26. As indicated in Table 26, these contributions can be categorized into three main groups.

The first category pertains to theoretical advancements in understanding digital transformation's impact on firms. This includes the development of a general equilibrium model that shows how digital transformation affects firms' exports through enhancements in capital and labour efficiencies (Contributions 1 and 2). It also involves applying the Firm-Specific Advantage theory to understand how digital transformation influences firms' export performance (Contribution 6) and utilizing the Resource-Based View to analyse how different directions of digital transformation affect firms' export behaviour (Contribution 8).

The second category relates to empirical findings and practical implications for firms and policymakers. This encompasses empirical evidence of how digital transformation affects firms' export performance (Contribution 5) and export behaviour (Contribution 9), as well as identifying the best digital strategies (Contribution 3). Furthermore, the research offers practical guidance for firms and policymakers on selecting appropriate digital transformation pathways to enhance global competitiveness (Contribution 10).

The third category involves methodological innovations that improve the quality of measurement and reliability of empirical results. This is achieved through the creation of a novel firm-year-level measurement of digital transformation using textual analysis (Contribution 4), employing LLM models to identify different directions of firms' digital transformation (Contribution 8), and developing new instrumental variables based on commuting distances and times (Contribution 7).

Collectively, these contributions enhance the theoretical framework, empirical understanding, and methodological approaches in studying the impact of digital transformation on firms.

Table 26. The summary of contributions

Chapter	Theoretical Contributions	Contributed To
Chapter 2	**1.** Creates a theoretical model showing how digital transformation affects exports through capital and labour efficiencies.	Theoretical models of digital transformation's impact on international trade; extensions of the Melitz model.
	2. Analyses how digital transformation differently impacts capital and labour efficiencies and optimal input ratios.	Studies on production efficiency and input optimization in the context of digital transformation.
	3. Demonstrates that optimal digital strategies vary with market competition; more digital transformation isn't always better.	Strategic management in varying competitive environments; literature on digital transformation strategy.
Chapter 3	**4.** Develops a new method to measure firms' digital transformation using text analysis of annual reports.	Measurement of digital transformation in firms; application of natural language processing in economics.
	5. Confirmed that digital transformation boosts export performance and introduced new firm grouping criteria based on efficiencies.	Empirical studies on digital transformation's impact; firm heterogeneity in international business.
	6. Analyses the effects with firm specific advantage theory under digital era, shows that digital transformation isn't universally beneficial.	Strategic management of digital transformation; cost-benefit analysis in digital adoption.
	7. Creates new instrumental variables based on commuting distances, improving causal inference in spatial economics.	Econometric methodology; development of instrumental variables in spatial economics.
Chapter 4	**8.** Distinguishes between management and production digital transformation using LLM model, analysing their positive effects on export diversification.	Resource-Based View (RBV) in digital transformation; export diversification strategies.
	9. Finds that management digital transformation reduces export concentration, while production digital transformation does not significantly affect market distribution.	Studies on export concentration and diversification; impact of digital transformation on export behaviours and preferences.
	10. Offers practical guidance for firms and policymakers on choosing digital transformation paths to enhance global competitiveness.	Strategic management in digital transformation; policy implications for international business.

5.3. Managerial and Societal Implications

The findings of this research offer significant implications for both firms and policymakers. For firms, the research underscores the importance of strategically aligning digital transformation initiatives with their specific market environments. The theoretical advancements demonstrate that digital transformation impacts export performance through enhancements in capital and labour efficiencies. However, the optimal level and type of digital adoption vary depending on the intensity of market competition. Excessive digitalization may not always be beneficial, especially in less competitive markets. Therefore, firms need to conduct thorough cost-benefit analyses to determine the appropriate extent of digital investment that maximizes profitability. Furthermore, distinguishing between management and production digital transformation is crucial. The studies reveal that management digital transformation not only enhances export diversification but also reduces export concentration, allowing firms to mitigate risks associated with over-reliance on specific markets. In contrast, production digital transformation improves export diversification without significantly affecting market distribution strategies. Firms should assess their internal resources and strategic objectives to select the most suitable digital transformation pathway, thereby optimizing their export behaviours and strengthening global competitiveness.

The methodological innovations, such as the novel firm-year-level measurement using textual analysis and the use of Large Language Models (LLMs) to identify digital transformation directions, provide firms with advanced tools to accurately assess and monitor their digital initiatives. Utilizing these tools can inform better decision-making and resource allocation.

For policymakers, the implications of this research call for a deeper, more granular digital governance agenda. Policymakers should move beyond general digital adoption campaigns and design policies that directly address sectoral needs, firm heterogeneity, and varying competitive contexts. Given that the optimal level and type of digital transformation depend heavily on market conditions, government programs must be responsive to where firms stand on the digital maturity curve. For example, digital tax credits or grants can be made conditional on market exposure, efficiency benchmarks, or transformation type (management vs. production). Importantly, management digital transformation should receive particular policy attention due to its macroeconomic externalities: it not only improves firm-level competitiveness but also enhances national export resilience by reducing systemic dependency on a small set of trade partners.

Policy support should also extend beyond financial incentives. Governments can actively create digital transformation ecosystems by investing in digital infrastructure, supporting managerial digital literacy through executive training, and facilitating data-sharing platforms to reduce the information gap faced by firms in emerging markets. Furthermore, the digital measurement techniques introduced in this thesis, including firm-year-level textual metrics, can serve as monitoring tools for public agencies to track policy effectiveness and benchmark sectoral progress. By leveraging these measurement innovations, policymakers can adopt a more evidence-based approach to refining national digital strategies.

In conclusion, digital transformation policy should be grounded in precision, flexibility, and long-term alignment with national economic priorities. Firms must optimize rather than maximize their digital investments based on strategic fit. Policymakers, in turn, should build adaptive, data-informed policy frameworks that recognize the heterogeneous value of digital transformation across firm types and transformation pathways. A tailored and well-governed digital transformation landscape has the potential to deliver not only firm-level competitiveness but also national-level trade diversification and economic resilience.

5.4. Limitations and Future Research

Several limitations of this research are discussed below and offered directions for future research. Firstly, the theoretical model focuses primarily on capital and labour as the production inputs affected by digital transformation. While this simplification enhances model tractability and clarity, it overlooks other inputs—such as technology, management practices, and organizational capital—that also exhibit heterogeneity in response to digital transformation. Incorporating a broader range of inputs into the production function could provide a more comprehensive understanding of how digital transformation impacts firms' production processes. Secondly, limitations in data availability and quality pose constraints on the empirical analyses. The relatively immature state of macroeconomic and market data in China prevented some parameters from being directly calibrated using Chinese market data. Similarly, the limited availability of corporate export customs data resulted in a sample covering only recent years. This restriction hinders the ability to observe the long-term effects of digital transformation on export performance and efficiency improvements. The heterogeneity analysis was also constrained by the sample size and the need to ensure effect identification within subgroups.

Methodologically, while the study employs innovative techniques such as textual analysis for measuring digital transformation, there is room for advancement. Applying more sophisticated and emerging natural language processing techniques could enhance the analysis of the mechanisms underlying digital transformation's effects. Additionally, as digital technologies and practices evolve rapidly, capturing these changes and studying their long-term impact on firms' internationalization strategies present significant challenges.

Future research could address these limitations by extending the theoretical model to include additional production inputs, thereby capturing a broader spectrum of heterogeneity in firms' responses to digital transformation. As China's market data become more mature and accessible, future simulations and calibrations can utilise this data for more accurate parameter estimation, enhancing the model's applicability. Expanding the dataset to include more extensive and longitudinal customs data would allow for examination of long-term effects and facilitate more granular heterogeneity analyses.

Moreover, employing advanced natural language processing methods could provide deeper insights into textual data, improving the precision of digital transformation measurements and the robustness of empirical findings. Investigating the impact of digital transformation on export behaviours across different industries and regions, especially in uncertain and volatile market environments, would also be valuable. Developing dynamic models and methodological approaches that account for the continuous evolution of digital transformation practices could help capture these changes and assess their long-term implications for firms' internationalization.

In conclusion, addressing these limitations in future studies will strengthen the theoretical and empirical foundations established in this thesis, offering a more nuanced understanding of the multifaceted effects of digital transformation on firms' export performance and behaviours.

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