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From Information Resources to Digital Productivity: Evaluating New-Quality Productive Forces through Information Infrastructure and Communication Systems

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Abstract

This study positions the notion of new-quality productivity (NQP) within the broader field of information science, examining how the alignment of information assets with communication infrastructures contributes to forms of digital productivity. It introduces an empirical framework that associates knowledge structuring, data stewardship, and informational circulation with measurable outputs captured through total factor productivity (TFP). Using data from Zhejiang Province for the period 2020–2023, the analysis applies a multi-input DEA-Shapley decomposition approach to apportion productivity gains to information-related elements (data valorisation, information asset development, analytical capacity) and communication-related components (ICT diffusion, platform interoperability, digital commercial activity). The findings reveal a mutually reinforcing relationship between informational and communicative functions, generating a cohesive and productive information environment. This aligns both with foundational perspectives in information-flow theory and with contemporary scholarship in knowledge management. The study fulfils an AJLAIS-oriented contribution by extending information science into empirical productivity research, offering evidence on how digital infrastructure, metadata regimes, and information interchange underpin sustainable innovation pathways and economic advancement.

Keywords: Information Science, Knowledge Management, Information Infrastructure, Communication Systems, Data Factorization, Digital Transformation, Information Governance, New-Quality Productivity (NQP), Total Factor Productivity (TFP), DEA–Shapley Model.

Introduction

NQP is best interpreted as a reconfiguration of how information resources are structured and circulated through communication infrastructures rather than simply a rebranded expression of economic expansion. In light of major shifts in developmental conditions, China's economy has moved from rapid expansion towards a phase centred on qualitative refinement, requiring the reorientation of development models, structural realignment, and renewed growth drivers (Han et al., 2024). Against this background, Xi Jinping introduced the concept of NQP in 2023

(Fan, 2023), presenting it as a strategic framework for sustaining high-quality development in the current era.

NQP departs fundamentally from earlier growth approaches and identifies scientific and technological innovation as its principal force. It represents a sophisticated form of productivity marked by advanced technologies, heightened efficiency, and enhanced performance quality (Fan, 2023). At its core, it involves reorganising labour, the instruments of labour, and the objects of labour. Its underlying rationale is the utilisation of innovation to remould industrial systems, supporting both the evolution of strategic and prospective industries and the intelligent, environmentally responsible modernisation of established sectors (Luo, 2024). Forming an updated application of Marxist productivity principles adapted to China's modernisation pathway (Zhang et al., 2024), NQP embodies technological transformation alongside institutional renewal and ecological imperatives (Qi, 2024). Rigorous assessment of NQP levels holds theoretical and practical relevance for evaluating regional development quality, guiding resource distribution, and supporting targeted policy interventions.

Because NQP encompasses a complex and multi-layered set of processes, its evaluation must rely on objective, quantifiable indicators. Scholars and policymakers generally identify TFP as the primary metric for this purpose (Shi and Sun, 2024). Originating from Solow's foundational growth framework, TFP measures the portion of output growth attributable to intangible determinants such as technological advancement, organisational adaptation, and managerial improvements, after isolating physical inputs like labour and capital. This residual, often labelled the Solow residual (Solow, 1957), marks the transition from input-driven expansion to innovation-based development. Nonetheless, mainstream TFP analyses rarely treat information resources and communication infrastructures as explicit, co-equal inputs, limiting the metric's ability to capture information-science dimensions. TFP therefore corresponds closely with NQP's defining features of innovation-oriented and quality-centred development (Cai and He, 2024). Establishing a TFP evaluation structure specifically aligned with NQP would allow movement from high-level conceptual discussion to empirically grounded inquiry (Gong and Yuan, 2024).

This study reconceptualises TFP as an output stemming from an information ecosystem and develops a DEA-Shapley framework that attributes productivity to information-type and communication-type determinants. Here, information-type elements refer to data resources, analytical capacity, and governance processes, while communication-type elements include ICT adoption, platform interconnectedness, and digital commercial activity. Within an information-science perspective, data are treated as information resources (Borgman, 2015; Buckland, 1991), while ICT infrastructures and digital transformation constitute communication systems that store, distribute, and enable the use of information (Castells, 2010; Star and Ruhleder, 1996). This perspective aligns NQP with the central aims of information science, illustrating how information and communication systems enhance knowledge productivity and organisational outcomes (Brynjolfsson and Hitt, 2000; Jorgenson and Stiroh, 2000). Consequently, the paper links digital economics with library and information science by illustrating that productivity gains reflect how societies curate information resources and architect communication networks (Davenport, 1998; Shannon and Weaver, 1949).

The study contributes in three respects: conceptually, by locating NQP within information-flow and knowledge-management theory and interpreting TFP as a product of an information ecosystem; methodologically, by merging information-type and communication-type variables into a DEA-Shapley structure; and empirically, by demonstrating with Zhejiang data (2020–2023) how data governance and ICT integration jointly affect measurable productivity. Accurate TFP measurement is essential for meaningful evaluation. Analytical approaches can be broadly classified into parametric and non-parametric techniques (Li et al., 2019). Parametric approaches, such as Stochastic Frontier Analysis (SFA), introduced by Aigner et al. (1977), estimate production frontiers by specifying a functional relationship, typically Cobb-Douglas or Translog. SFA's advantage lies in its ability to separate random shocks from technical inefficiency, offering robustness to statistical noise (Färe and Grosskopf, 1985). However, SFA requires strong assumptions about functional form and the statistical distribution of inefficiency (e.g., half-normal, truncated-normal), assumptions that may be misaligned with real-world production systems (Horrace and Wang, 2022). For NQP—a system grounded in disruptive innovation, rapid technological shifts, and non-linear dynamics—such assumptions can distort results and diminish interpretive value (Kumbhakar et al., 2019; Zhang, 2024).

Non-parametric methods, particularly Data Envelopment Analysis (DEA) developed by Charnes et al. (1978), avoid these limitations by deriving empirical production frontiers through linear programming without presupposing functional shapes or error distributions. DEA is highly suitable for analysing systems with unpredictable or emerging technological trajectories (Seiford and Thrall, 1990). Its advantages for NQP include modelling multi-input–multi-output relationships, reliance on minimal axioms, applicability to strategic and evolving industries, and the possibility of decomposing efficiency to reveal underlying mechanisms. Although research on NQP is expanding, agreement on how to measure it remains limited. Variations across indicator systems and conceptual frameworks lead to divergent assessments. Clarifying the relationships between its structural foundations, innovation mechanisms, and core metrics remains essential for understanding its influence on TFP.

While TFP growth is often treated as a manifestation of NQP, using TFP as an evaluative structure requires improved methods of attribution. DEA is widely adopted for this purpose due to its capacity for decomposing efficiency components. Traditional DEA-based decompositions distinguish technical efficiency, pure technical efficiency, scale efficiency, and allocative efficiency, offering insight into performance structures and guiding data-based policy design. Banker et al. (1984) partitioned technical efficiency into pure technical and scale effects; Charnes et al. (1991) introduced a diagnostic classification of efficient and inefficient DMUs and linked scale inefficiencies to specific drivers. Real production systems, however, often involve sequential or multistage operations. This prompted Kao and Hwang (2008) to develop a two-stage DEA model, enabling stage-level decomposition. Network DEA extensions followed, most notably the slack-based measure model of Tone and Tsutsui (2009), which evaluates subsystem and system-wide efficiency through slack analysis. Kao (2009) and Kao and Hwang (2010) further generalised DEA to handle serial, parallel, dynamic, and information-technology-driven structures. Foundational works by Byrnes et al. (1984) and Färe et al. (1994) separated productivity growth into technical change and scale components. Nemoto and Goto (2003) applied dynamic DEA to electricity firms, showing how long-term asset commitments influence productivity patterns.

Meta-frontier (MF) techniques, introduced by Battese et al. (2004), allow comparison across groups with heterogeneous technologies by measuring the gap between group frontiers and a universal frontier. O'Donnell et al. (2008) expanded the MF framework using both DEA and SFA, enabling decomposition into inter-group efficiency and technological gap ratios. Together, these advancements have transformed DEA from a static two-component tool into an extensive suite of multi-stage, network, dynamic, and cross-group decomposition methods capable of analysing complex systems. However, even advanced models struggle to reflect the intricacies of data-driven innovation. For example, the widely used framework by Färe et al. (1994) includes technological progress as a factor but cannot fully capture data-centric mechanisms.

Addressing these limitations requires rethinking TFP measurement from the standpoint of data factorisation. This involves explicitly recognising data as a production input and disaggregating productivity at the input level. Such a perspective would permit clearer examination of how data resources contribute to efficiency gains and whether their allocation is equitable or optimal. Recent attempts to construct indicator systems based on classical categories such as labour, tools, and objects of labour aim to describe productivity transformation through concepts like new-quality labour, new-quality tools, and resource allocation efficiency (Ding et al., 2024; Dong, 2024; Xin et al., 2024). Yet these systems often lack definitional clarity, logical consistency, and precise attribution mechanisms. To date, no robust decomposition model directly operates at the input–output indicator level. This study therefore extends output-oriented DEA decomposition to the level of individual inputs, separately measuring land, labour, capital, and data productivity. In practice, labour productivity is frequently substituted for NQP, but the validity of this replacement is unclear and forms a core focus of this investigation.

Prior literature describes that Statistical Bulletin, NQP in the province has grown steadily. The added value of the so-called three new economy—emerging industries, new business formats, and new organisational modes—is projected to reach 28.5 per cent of regional output (Guangqin and Mengjiao, 2024). The digital economy's core industries produced

1,106 billion yuan in added value, an 8.1 per cent increase. Given this context, the present study examines Zhejiang's regional data for 2020–2023, incorporates data as explicit inputs in the DEA framework, and employs the Shapley value method to systematically decompose TFP. By constructing an evaluation system consistent with NQP characteristics, the study aims to clarify the mechanisms connecting NQP with TFP and provide empirical guidance for improving productivity and optimising strategic resource allocation.

Building on this information-science approach, the study conceptualises NQP as a form of productivity rooted in the structuring and circulation of information within communication systems. Rather than treating TFP solely as an economic metric, it views TFP as the measurable consequence of how effectively information resources—namely data, analytical capabilities, and knowledge—are generated, controlled, and disseminated through digital and communicative infrastructures. This perspective links foundational information-flow theory (Shannon and Weaver, 1949) with contemporary knowledge-management theory (Borgman, 2015; Davenport, 1998), framing NQP as an information ecosystem in which information-type and communication-type factors jointly influence digital transformation. Through the DEA-Shapley model, the study provides an empirical means of evaluating how information and communication capacities shape productivity and innovation outcomes across regions.

Following this conceptual grounding, the subsequent section outlines the methodological design employed to operationalise these ideas and describes how information-type and communication-type elements are incorporated into the DEA-Shapley framework to measure and decompose TFP at the regional level.

Materials and Methods

Data Sources

This study adopts 2020–2023 as the observation window. The empirical analysis is developed from primary data sourced mainly from the Zhejiang Statistical Yearbooks (2021–2024), while the estimation of capital stock relies on the statistical yearbooks of individual prefectures. Owing to the province's distinctive landscape, widely summarised as comprising seven parts mountains, one-part water, and two parts cultivated land, regional land availability is limited. For this reason, land and data elements are explicitly incorporated into the analytical framework. The dataset covers GDP, land, labour, capital, and data-related variables for ten prefecture-level regions in Zhejiang. From an information-science standpoint, the chosen indicators embody the dual structure of digital productivity. The informational layer reflects the existence, accessibility, and governance of data as informational objects, while the communicative layer concerns the structures through which information is transmitted and operationalised (Borgman, 2015; Buckland, 1991; Castells, 2010; Shannon and Weaver, 1949). Within this two-tiered perspective, the empirical model is aligned with the logic of an information-ecosystem, where data stewardship and communication infrastructures jointly shape NQP outcomes.

Land input is measured by each region's total land area, and labour input by the number of employed persons. Land shows minimal temporal variation, except in the case of Zhoushan. Capital stock is approximated through the perpetual inventory method. The GDP deflator (base year 1978) is used to derive the investment price index, following Sun et al. (2010), and depreciation is set at 9.6% in accordance with Zhang et al. (2004). Quantifying data elements poses inherent challenges because it relates simultaneously to data creation, utilisation, and dissemination, dimensions usually captured by composite indicator frameworks (Tao and Xu, 2021). Here, four Internet-related indicators are used to represent data elements: fixed broadband access ports, mobile Internet users, mobile Internet data traffic, and fixed broadband subscribers. Correlation analysis using panel data for eleven regions over 2020–2023 indicates very strong linear associations, with coefficients between 0.9522 and 0.9954. PCA based on the correlation matrix yields a first principal component with an eigenvalue of 3.9272, accounting for 98.18% of total variance. The loadings range from 0.4928 to 0.5035, signalling near-uniform contribution among indicators. Given this structure, mobile Internet data traffic is selected as the representative proxy for regional data elements. The corresponding indicator values are reported in Table 1. To ensure intertemporal comparability, regional GDP values are deflated using the provincial GDP deflator.

Table 1: Statistical Characteristics of Input-output Indicators.

Indicators	GDP	Land	Labor	Capital	Data
Mean	1234.40	9608.89	353.64	4367.16	132797.50
Median	1062.83	9816.00	330.18	3786.53	121479.50
Maximum	3576.51	17275.00	770.02	10766.84	367021.90
Minimum	289.20	1459.00	72.14	1227.28	18089.00
Standard deviation	938.42	4638.22	208.31	2597.90	93691.71
Skewness	1.15	0.09	0.44	0.86	0.62
Kurtosis	3.30	2.40	2.21	2.76	2.45

Note: GDP is measured at 1978 prices in billion yuan, land in square kilometers, labor in ten thousand people, capital at 1978 prices in billion yuan, and data in ten thousand GB.

Within the NQP framework adopted in this study, the Internet-related indicators constitute the informational layer, representing the availability and circulation of data as an information resource (Borgman, 2015; Buckland, 1991). To capture the wider digital environment, the communication layer is represented by ICT- and digital-transformation indicators, such as enterprise website coverage, e-commerce participation, and the level of computerisation. These reflect the infrastructures and platforms through which information is transmitted, coordinated, and transformed into productive outputs (Castells, 2010; Shannon and Weaver, 1949; Star and Ruhleder, 1996). This dual-layer indicator system treats information and communication as co-equal inputs, consistent with evidence that ICT-enabled communication enhances the value of information resources and strengthens organisational and economic performance (Brynjolfsson and Hitt, 2000; Jorgenson and Stiroh, 2000). It therefore allows the direct attribution of digital-factor contributions to TFP rather than relegating them to unexplained residuals.

Methodology

Anchored within the broader shift toward data factorisation in contemporary digital systems, this study develops a measurement approach that aligns the assessment and decomposition of TFP with the defining attributes of NQP. The central aim is to establish an evaluation framework that reflects the conceptual architecture of NQP while clarifying its fundamental connection to TFP. The empirical component utilises region-level evidence from Zhejiang Province, analysing how TFP outcomes correspond to NQP-related indicators across its constituent areas. From an information-science standpoint, the methodological structure treats the production environment as an interlinked information-communication system in which inputs encompass both the generation of data resources and the infrastructures that enable their movement, coordination, and transformation into measurable productive outputs.

Methodologically, the analysis combines multi-indicator evaluation, DEA, and the Shapley value decomposition technique derived from cooperative game theory. DEA is first used to estimate regional TFP without imposing any pre-specified functional form, thereby identifying the multi-factor frontier of input–output relations. The Shapley value procedure is subsequently employed to allocate proportional contributions across input dimensions, with particular attention to the data factor, thus quantifying the marginal impact of each emergent production element on TFP dynamics. The methodological rationale lies in integrating DEA's efficiency-based estimation with the equitable attribution features of Shapley values. This synthesis strengthens the interpretative clarity and traceability of the results while preserving the model's robustness. More importantly, it enables the analytical structure to emulate the interactive characteristics of information and communication processes, positioning TFP as a measurable outcome of information-system performance and communicative capability within digital-sector production.

The framework conceptualises knowledge infrastructures as measurement units structured around information and communication (Borgman, 2015; Star and Ruhleder, 1996). Variables such as data factorisation, broadband access, and mobile data volume represent the depth, accessibility, and operational readiness of information resources, as understood in information-type terms (Borgman, 2015; Buckland, 1991). Complementary communication-type indicators, including ICT penetration, e-commerce activity, and enterprise digital transformation, illustrate the mechanisms by which information is transmitted, coordinated, and rendered operational within production networks (Castells, 2010; Shannon and Weaver, 1949). On this basis, the model is structured to determine not only productive efficiency but also the embedded information–communication capability that forms a core element of NQP. Through the DEA–Shapley attribution design, marginal contributions are systematically distributed across the full range of inputs (Charnes et al., 1978; Färe et al., 1994; Shapley, 1953). In doing so, the operationalisation of indicators and successive decomposition stages jointly represent information-type (data, analytics, governance) and communication-type (ICT, platform integration, e-commerce) variables as the twin structural pillars of NQP within the DEA–Shapley analytical system.

Multi-Indicator Measurement of New-Quality Productivity (NQP)

As shown in Figure 1, the assessment of NQP development spans several interlinked dimensions, including its conceptual grounding, operative drivers, industrial foundations, defining markers, and intended developmental outcomes. A rigorous understanding of how these components relate to one another is necessary for formulating an evaluation system that is coherent and analytically sound. Consistent with the strategic orientation of NQP, the present study places particular emphasis on the connections between its core markers and the accompanying supportive dimensions. The analysis seeks to clarify the channels through which NQP contributes to improvements in TFP, thereby informing the construction of an institutional framework capable of sustaining innovation-led and quality-focused patterns of economic progress.

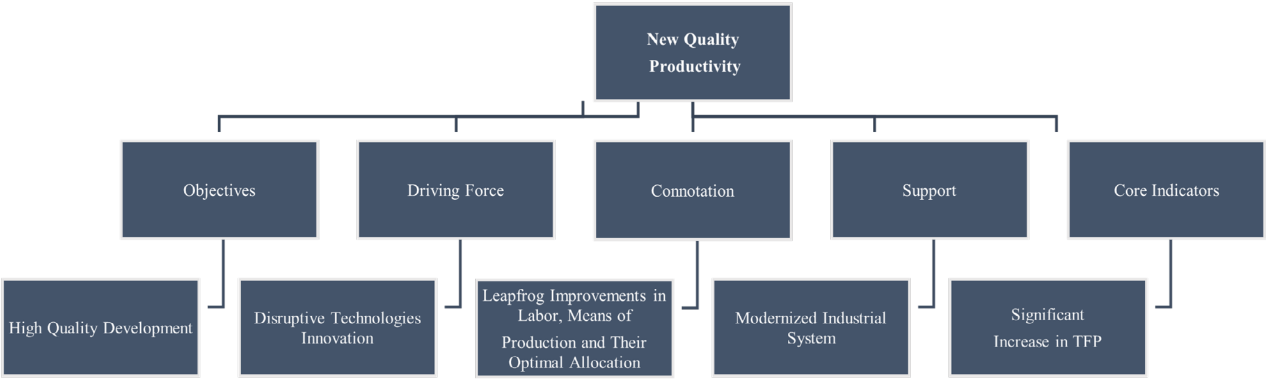

Figure 1: Evaluation Dimensions of the Development Level of New Productive Forces.

Measurement and Decomposition of Total Factor Productivity (TFP)

In this research, TFP is assessed and decomposed using the DEA approach. The decision-making units (DMUs) examined in the analysis are defined as follows:

$$(x_j, y_j),\ j = 1, 2, \cdots, n \quad (1)$$

Where x_j *is the input column vector of the j-th DMU, and* y_j *is the corresponding output column vector. For clarity, we denote the input and output of the target DMU as* x_0 *and* y_0*, respectively, with the target DMU being one of the DMUs under evaluation.*

The Constant Returns to Scale (CRS) framework introduced by Charnes et al. (1978) represents one of the foundational DEA formulations and is applied to estimate Technical Efficiency (TE). Within this setting, TE is expressed as the reciprocal of the optimal solution to the following optimisation problem:

$$\begin{cases} \max & z \\ \text{s.t.} & \sum_{j=1}^{n} \lambda_j x_j \le x_0 \\ & \sum_{j=1}^{n} \lambda_j y_j \ge z y_0 \\ & \lambda_j \ge 0,\ j = 1, 2, \cdots, n \end{cases} \quad (2)$$

Here, $1/\tilde{z}$ *represents the efficiency score of the target DMU. If* $\tilde{z} = 1$*, the DMU is deemed weakly DEA-efficient.* This specification quantifies the extent to which outputs can be proportionally increased without affecting input levels. The corresponding dual representation of the CRS model is given by:

$$\begin{cases} \min & w^T x_0 \\ \text{s.t.} & w^T x_j - u^T y_j \ge 0,\ j = 1, 2, \cdots, n \\ & u^T y_0 = 1 \\ & w \ge 0,\ u \ge 0 \end{cases} \quad (3)$$

In this dual representation, w and u are vectors of weights for inputs and outputs, respectively. These optimisation variables demonstrate DEA's endogenous weighting property, whereby weights are internally assigned for each DMU to maximise its efficiency score. Consequently, the evaluation benchmarks differ between DMUs, which is a frequently cited methodological limitation in DEA studies. To accommodate Variable Returns to Scale (VRS), Banker et al. (1984) proposed a revised formulation that separates Pure Technical Efficiency (PTE). The associated optimisation problem is expressed as follows:

$$\begin{cases} \max & z \\ \mathrm{s.t.} & \sum_{j=1}^{n} \lambda_j x_j \le x_0 \\ & \sum_{j=1}^{n} \lambda_j y_j \ge z y_0 \\ & \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \ge 0, j = 1,2,\cdots,n \end{cases} \tag{4}$$

Scale Efficiency (SE) is calculated based on the relationship between TE and PTE, and is expressed as:

$$\mathrm{TE} = \mathrm{PTE} \times \mathrm{SE}$$

Significant growth in TFP represents a defining feature of NQP. To evaluate changes in TFP over time, this study utilises the Malmquist Productivity Index (Färe et al., 1994), which is defined as follows:

$$M\left(x^{t+1},\ y^{t+1}, x^t,\ y^t\right) = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{0.5} \tag{5}$$

The Malmquist index model requires intertemporal efficiency comparisons and must be estimated using panel data. In this framework, the superscript t corresponds to the time period of each DMU, where $D^t(x,y)$ *represents the relative efficiency of the target DMU (x,y) evaluated against the production frontier of period. For instance, under the CRS technological assumption, the efficiency measure* $D^t(x_0^{t+1}, y_0^{t+1})$ *is determined by the following optimization model:*

$$\begin{cases} \max & z \\ \mathrm{s.t.} & \sum_{j=1}^{n} \lambda_j x_j^t \le x_0^{t+1} \\ & \sum_{j=1}^{n} \lambda_j y_j^t \ge z y_0^{t+1} \\ & \lambda_j \ge 0, j = 1,2,\cdots,n \end{cases} \tag{6}$$

In other words, this approach evaluates the performance of target DMU in period t+1 against the production frontier established in period t. Under this specification, the ratio of intertemporal relative efficiency scores i.e., $\frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}$*, captures the efficiency change between periods.*

By decomposing TE, the Malmquist index allows for the evaluation of temporal variations in technology, technical efficiency, pure technical efficiency, and scale efficiency. In particular, under the CRS assumption, Equation (5) represents the intertemporal technological change as the geometric mean of relevant ratios. *Technical progress is identified if the Malmquist index* $M(x^{t+1}, y^{t+1}, x^t, y^t) > 1$*, indicating technological improvement.* Within the framework of data factorisation, employing DEA to quantify TFP introduces specific challenges, notably in selecting the most suitable model. There remains no consensus regarding the production properties of data factors, particularly in terms of their returns to scale. This study incorporates all relevant production inputs in the measurement of TFP, estimating regional TFP under the CRS assumption, while integrating the theoretical insights of McKenzie (1959) and Beniger (1986).

Shapley Model

Consider a cooperative game defined by a set of players $\Gamma = \{1,2,\cdots,m\}$ *and a characteristic function v, which assigns to each coalition* $S \subseteq \Gamma$ *a value in* $\mathbb{R}$*. The Shapley value (Shapley, 1953), which allocates payoffs to each player, is computed as follows:*

$$\Phi_i(m, v) = \sum_{S \subseteq \Gamma \setminus \{i\}} \frac{|S|!(m-|S|-1)!}{m!} [v(S \cup \{i\}) - v(S)] \tag{7}$$

Where $\Gamma/\{i\}$ *denotes the set of all players excluding player i, while |S| represents the cardinality of coalition S. The computation of Shapley values fundamentally requires the specification of a valid characteristic function v(S). This function must satisfy weak monotonicity, formally, for any two coalitions where* $S \supset T$*, the condition* $v(S) \ge v(T)$ *must hold. This property ensures that each player i's marginal contribution, defined as* $v(S \cup \{i\}) - v(S)$*,* remains non-negative. Accordingly, the Shapley value distributes returns to all participants by computing an axiomatic, weighted average of their individual marginal contributions.

In this study, DEA is integrated with the Shapley model to decompose TFP, allowing for the allocation of appropriate returns to each production factor. In this context, single-factor productivity is defined and measured, providing a basis to evaluate NQP development across its core dimensions. The operationalisation employs the two-tiered information-ecosystem framework, estimating the contributions of information-type and communication-type inputs to overall factor productivity across Zhejiang's regions using the DEA–Shapley methodology.

Evaluation and Decomposition of Total Factor Productivity (TFP)

This section applies the DEA approach to measure and decompose TFP for each region of Zhejiang Province over the period 2020–2023. The procedure follows several key steps. First, consistent with the data factorisation perspective in the digital era, a multidimensional input–output index system is constructed that explicitly incorporates data factors. Changes in TFP across regions are then calculated using the Malmquist Index. By isolating the effects of technological progress, regions at different time points are treated as distinct DMUs, effectively expanding the sample and improving the resolution of TFP measurement. Second, regional TFP levels are systematically evaluated within a multi-criteria framework, capturing the aggregate contribution of new-quality factors to output efficiency. Finally, the Shapley value (Shapley, 1953) from cooperative game theory is employed to decompose TFP, allowing for the definition and measurement of single-factor productivity and the assessment of the marginal impact of data factors and other critical inputs on efficiency improvements.

DEA Input-Output Indicator System

This study utilises a multi-input, single-output indicator framework to define the production system, with the eleven regions of Zhejiang Province treated as DMUs. The four categories of production inputs—land, labour, capital, and data—are considered for each DMU annually, with GDP serving as the output. Relevant indicator values are presented in Table 1, where regional GDP figures are deflated using the provincial GDP deflator for the corresponding years. Assuming producer equilibrium, inputs are allocated optimally, and intrinsic correlations often exist among the various production factors. Simple correlation coefficients were calculated for the four inputs, with results reported in Table 2. Findings reveal that data elements are significantly and linearly correlated with land, labour, and capital, showing particularly strong associations with labour and capital. The generation of data factors depends on traditional inputs, which function as essential carriers for data creation at a practical level. Moreover, the effectiveness of data factors relies on the support of conventional production inputs. Conversely, in the digital era, traditional factors increasingly integrate with data inputs, demonstrating a pronounced data-oriented orientation and contributing to the qualitative transformation of conventional production factors.

Table 2: Correlation between Production Factors.

		Land	Labor	Capital	Data
Land	Pearson correlation	1	0.4948	0.3767	0.4198
	Significance (two-side)		0.0006	0.0117	0.0046
	N	44	44	44	44
Labor	Pearson Relevance	0.4948	1	0.9472	0.9273
	Significance (two-side)	0.0006		0.0000	0.0000
	N	44	44	44	44
Capital	Pearson Relevance	0.3767	0.9472	1	0.9135
	Significance (two-side)	0.0117	0.0000		0.0000
	N	44	44	44	44
Data	Pearson correlation	0.4198	0.9273	0.9135	1
	Significance (two-side)	0.0046	0.0000	0.0000	
	N	44	44	44	44

Note: The unit of GDP is 1978 price of 100 million yuan, the unit of land is square kilometer, the unit of labor is 10,000 people, and the unit of capital is 1978 price 100 million yuan, while the data unit is 10,000 gigabytes.

Table 3: Malmquist Index of Various Regions in Zhejiang Province from 2020–2023.

Area	Changes in Efficiency	Technology Changes	Pure Technical Efficiency Change	Scale Efficiency Changes	TFP Change
Hangzhou	0.997	0.962	1.000	0.997	0.959
Ningbo	1.000	0.980	1.000	1.000	0.980
Wenzhou	0.990	0.975	0.978	1.013	0.965
Jiaxing	0.998	1.050	1.000	0.998	1.048
Huzhou	1.001	0.904	0.976	1.026	0.905
Shaoshing	0.988	0.892	0.990	0.998	0.881
Jinhua	0.983	0.982	0.968	1.016	0.966
Quzhou	0.983	0.871	1.000	0.983	0.856
Zhoushan	1.000	0.972	1.000	1.000	0.972
Taizhou	0.983	0.982	0.969	1.015	0.965
Lishui	0.999	0.886	1.000	0.999	0.886
Mean	0.993	0.949	0.989	1.004	0.943

Malmquist Index

Recognising that NQP is fundamentally propelled by disruptive technological innovation, this section first evaluates whether substantial technological progress occurred over the observation period. Treating the eleven regions as DMUs and conducting the analysis on an annual basis, the DEAP Version 2.1 software was employed to compute the Malmquist Index. The results are summarised in Table 3, with the mean values representing simple arithmetic averages across all regions. The results indicate that technological progress during the observation period is not statistically significant across the regions. Comparable outcomes are observed when the Malmquist Index is calculated using two-year intervals, confirming the robustness of the findings. These results suggest that, even in Zhejiang Province—a region with relatively advanced economic development—empirical support for General Secretary Xi Jinping's statement that "NQP has already taken shape in practice" is limited. Similarly, the minimal annual fluctuations in TFP constrain its effectiveness as an indicator for capturing the impact of emerging productivity developments.

Table 4: TFP and its Decomposition in Various Regions of Zhejiang Province from 2020–2023.

Year	**Area**	**TFP**	**Land**		**Labor**		**Capital**		**Data**	
			Productivity	**Equity**	**Productivity**	**Equity**	**Productivity**	**Equity**	**Productivity**	**Equity**
2020	Hangzhou	1.0000	0.1543	475.19	0.2278	701.75	0.3304	1017.77	0.2876	885.89
	Ningbo	1.0000	0.2237	530.91	0.2043	484.79	0.2814	667.94	0.2906	689.84
	Wenzhou	0.6662	0.0916	180.69	0.1339	264.11	0.2762	544.88	0.1645	324.54
	Jiaxing	0.9475	0.3126	347.76	0.1617	179.90	0.2236	248.74	0.2495	277.51
	Huzhou	0.8491	0.0880	63.46	0.1728	124.61	0.2445	176.29	0.3438	247.90
	Shaoshing	1.0000	0.1160	133.12	0.1905	218.61	0.2305	264.58	0.4631	531.51
	Jinhua	0.8501	0.0693	73.33	0.1349	142.74	0.5023	531.62	0.1437	152.05
	Quzhou	0.8851	0.0296	10.50	0.1496	52.99	0.2152	76.22	0.4907	173.79
	Zhoushan	1.0000	0.1883	54.45	0.2494	72.12	0.1110	32.09	0.4514	130.54
	Taizhou	0.8350	0.0842	101.47	0.1460	176.06	0.3998	481.98	0.2050	247.14
	Lishui	0.7957	0.0143	5.28	0.1311	48.54	0.2830	104.78	0.3673	135.96
	Total	0.8222	0.0984	1482.29	0.1813	2730.52	0.2952	4446.28	0.2474	3726.83
2021	Hangzhou	0.9983	0.1702	561.18	0.2584	851.84	0.3535	1165.51	0.2161	712.45
	Ningbo	1.0000	0.2571	682.05	0.2359	625.62	0.2977	789.64	0.2093	555.06
	Wenzhou	0.6389	0.1001	215.89	0.1480	319.37	0.2740	591.15	0.1168	252.02
	Jiaxing	0.9218	0.3243	406.33	0.1848	231.51	0.2550	319.45	0.1577	197.62
	Huzhou	0.7825	0.0958	81.09	0.2227	188.52	0.2316	196.06	0.2324	196.74
	Shaoshing	0.8929	0.1264	174.76	0.2379	329.08	0.2294	317.27	0.2992	413.75
	Jinhua	0.8435	0.0768	88.60	0.1533	176.86	0.5088	586.95	0.1047	120.76
	Quzhou	0.7216	0.0322	15.24	0.1648	77.85	0.2193	103.63	0.3052	144.21
	Zhoushan	0.9588	0.2187	70.63	0.3239	104.61	0.1086	35.07	0.3076	99.36
	Taizhou	0.8052	0.0889	116.14	0.1660	216.71	0.4004	522.85	0.1499	195.79
	Lishui	0.6556	0.0150	7.13	0.1374	65.12	0.2790	132.26	0.2241	106.25
	Total	0.8211	0.1073	1745.57	0.2126	3458.67	0.3185	5181.45	0.1828	2974.29
2022	Hangzhou	0.9590	0.1783	620.49	0.2722	947.32	0.3330	1159.03	0.1754	610.56
	Ningbo	1.0000	0.2796	781.30	0.2564	716.69	0.2870	802.03	0.1770	494.76
	Wenzhou	0.6129	0.1070	249.39	0.1564	364.76	0.2528	589.36	0.0967	225.55
	Jiaxing	0.9471	0.3582	453.55	0.1969	249.32	0.2608	330.29	0.1312	166.15
	Huzhou	0.7759	0.0993	87.71	0.2579	227.71	0.2215	195.57	0.1973	174.18
	Shaoshing	0.8950	0.1368	200.02	0.3017	441.02	0.2246	328.37	0.2318	338.82
	Jinhua	0.7845	0.0798	100.73	0.1594	201.07	0.4610	581.69	0.0843	106.35
	Quzhou	0.6673	0.0337	18.01	0.1998	106.75	0.1992	106.40	0.2346	125.30
	Zhoushan	0.9952	0.2628	91.68	0.3724	129.92	0.1125	39.24	0.2476	86.38
	Taizhou	0.7648	0.0925	130.04	0.1746	245.38	0.3732	524.58	0.1246	175.09
	Lishui	0.6248	0.0158	8.23	0.1500	78.23	0.2709	141.28	0.1882	98.12
	Total	0.7999	0.1133	1962.07	0.2312	4003.28	0.3045	5272.19	0.1508	2610.90
2023	Hangzhou	0.9800	0.1949	711.25	0.2944	1074.43	0.3340	1218.89	0.1567	571.94
	Ningbo	1.0000	0.3002	880.57	0.2699	791.87	0.2737	802.98	0.1562	458.15
	Wenzhou	0.6231	0.1191	297.60	0.1746	436.29	0.2425	605.99	0.0868	216.85
	Jiaxing	0.9944	0.4023	509.44	0.2094	265.18	0.2649	335.41	0.1178	149.12
	Huzhou	0.7740	0.1056	97.70	0.2860	264.53	0.2143	198.20	0.1681	155.45
	Shaoshing	0.8966	0.1483	229.84	0.3387	524.73	0.2271	351.88	0.1824	282.68
	Jinhua	0.7653	0.0892	124.99	0.1792	250.99	0.4231	592.59	0.0737	103.19
	Quzhou	0.6782	0.0358	20.02	0.2434	135.98	0.1919	107.22	0.2070	115.66
	Zhoushan	1.0000	0.2773	103.88	0.4107	153.83	0.1123	42.06	0.1997	74.83
	Taizhou	0.7520	0.0983	145.44	0.1820	269.34	0.3718	550.17	0.0999	147.82
	Lishui	0.6046	0.0170	9.82	0.1660	96.17	0.2430	140.75	0.1786	103.44
Total		0.8033	0.1229	2251.86	0.2516	4611.03	0.2993	5484.14	0.1295	2372.15

Note: TFP and single-factor productivity are both dimensionless, while the unit of each factor's equity is expressed in constant 1978 prices, with the unit being 100 million yuan.

Multi-criteria Measurement of TFP

In light of the limited evidence for technological progress, this study treats regions across different periods as separate DMUs to expand the number of units, thereby enhancing the discriminative capacity of TFP measurement. To provide a comprehensive provincial-level perspective, data from all regions in a given year are aggregated to form a new DMU. This aggregated DMU is incorporated into the analysis, with its efficiency value representing the provincial average TFP. It should be noted that under the CRS assumption, DMUs derived from aggregated data generally appear inefficient. Nonetheless, this procedure does not alter the TFP measurement standards nor affect the TFP of individual regions; it serves primarily to enable comparative evaluation against the provincial mean.

The traditional DEA approach suffers from limited differentiation because the linear programming solution may not be unique, resulting in variable evaluation criteria across DMUs. To overcome this limitation, multiple DEA models are constructed based on the specified input–output index system, allowing for a multi-criteria assessment of TFP in accordance with Cinca and Molinero (2004). Specifically, fifteen distinct DEA models are formulated: four single-input models, six dual-input models, four triple-input models, and one four-input model, considered the full or original model, illustrated in Figure 2. Owing to the endogenous weighting property of DEA, these models do not differ in principle. All fifteen models represent specific variants of the DEA evaluation criteria. For instance, the 1O model, which employs land as the sole input, is fundamentally equivalent to the full model (1234O) with the exception that the weights for labour, capital, and data are set to zero. Variations in assumptions and model specifications generate differences in TFP outcomes across the fifteen models, as shown in Exhibit 1. For clarity, efficiency indicators are labelled according to the DEA model employed; for example, the efficiency derived from the 1O model is referred to as 1O efficiency. These observations underscore that, to accurately characterise NQP development through its core markers, a well-defined TFP measurement standard is a prerequisite.

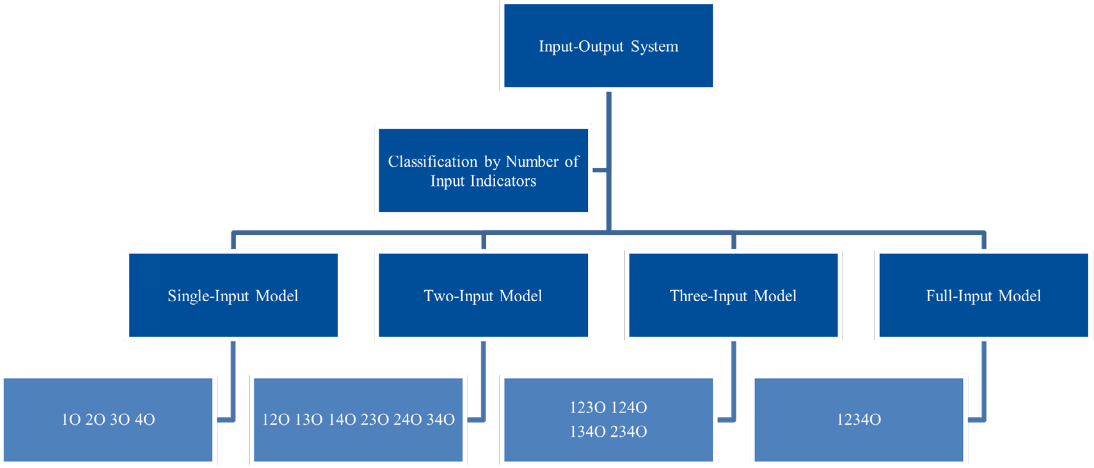

Figure 2: Subdivision of DEA Input and Output Index System (1 for land, 2 for labor, 3 for capital, 4 for data, and O for GDP).

Decomposition of TFP

Building on the multi-criteria assessment of TFP, this section utilises the Shapley cooperative game framework to decompose DEA efficiency, estimate the effective contribution of each production factor, and define and measure single-factor productivity accordingly. This procedure also facilitates the equitable allocation of each factor's contribution to overall productivity. In the implementation of Equation (7), the four production factors—land, labour, capital, and data—are conceptualised as players in the cooperative game. Any subset of these factors forms a coalition, with the efficiency derived from the associated DEA model representing the characteristic function of the game. Within this structure, the Shapley value of each factor is calculated, enabling a fair distribution of efficiency gains. These Shapley values are interpreted as the productivity of individual factors, namely land productivity, labour productivity, capital productivity, and data productivity.

When adopting Shapley values, the digital environment is considered in terms of information-type and communication-type factors, allowing the marginal impact of each to be evaluated relative to traditional inputs (Färe et al., 1994; Shapley, 1953). This organisation provides an empirical basis for testing the assumption that communication (ICT/digitalisation) functions as the mechanism through which information resources (data elements) are transformed into productivity, rather than treating digital inputs as a homogeneous entity (Brynjolfsson and Hitt, 2000; Castells, 2010; Shannon and Weaver, 1949). DEA efficiency, integrated with Shapley attribution, yields factor-specific contributions to output, revealing how information potential is converted into realised gains via communication capacity (Charnes et al., 1978; Färe et al., 1994).

The computational procedure is detailed in Appendix 2, with results presented in Table 4. A linear correlation exists among the production factors, and correspondingly, statistically significant linear relationships are observed between certain single-factor productivity measures. As shown in Table 5, land productivity is significantly and positively associated with labour productivity, whereas labour productivity and data productivity both exhibit significant negative correlations with capital productivity. These correlations are significant at a threshold of 0.0013 or lower. It is evident that the single-factor productivity concept applied here diverges from traditional definitions. In this study, single-factor productivity is derived through systematic TFP decomposition, capturing the marginal returns of individual production factors under varying technological conditions. By contrast, conventional labour productivity is typically expressed as GDP per capita, a broad measure lacking precision, and produces results substantially different from those obtained in this analysis. The single-factor productivity measures presented are dimensionless relative values. However, given the output-oriented nature of DEA efficiency, a correspondence exists between TFP and the single output indicator (GDP). Consequently, the relative contribution of each production factor can be inferred from its share of single-factor productivity within TFP, enabling a systematic decomposition of GDP by productivity levels. The resulting calculations are provided in Table 4.

Table 5: Correlation Analysis of Single-Factor Productivity.

		Land	Labor	Capital	Data
Land	Pearson correlation	1	0.4702	-0.2375	-0.1228
	Significance (two-side)		0.0013	0.1206	0.4270
	N	44	44	44	44
Labor	Pearson Relevance	0.4702	1	-0.5161	0.0693
	Significance (two-side)	0.0013		0.0003	0.6548
	N	44	44	44	44
Capital	Pearson Relevance	-0.2375	-0.5161	1	-0.4988
	Significance (two-side)	0.1206	0.0003		0.0006
	N	44	44	44	44
Data	Pearson correlation	-0.1228	0.0693	-0.4988	1
	Significance (two-side)	0.4270	0.6548	0.0006	
	N	44	44	44	44

Table 6: Results of Paired-Sample t-Tests for TFP (2020–2023).

TFP	Mean	Std.Dev.	Std.Error	95% CI (Lower)	95% CI (Upper)	t-value	df	p-value
2020 - 2021	0.0509	0.0566	0.0163	0.0149	0.0868	3.1144	11	0.0098
2020 - 2022	0.0687	0.0679	0.0196	0.0256	0.1118	3.5074	11	0.0049
2020 - 2023	0.0650	0.0762	0.0220	0.0165	0.1134	2.9518	11	0.0132
2021 - 2022	0.0178	0.0300	0.0087	-0.0012	0.0369	2.0583	11	0.0641
2021 - 2023	0.0141	0.0416	0.0120	-0.0123	0.0405	1.1733	11	0.2654
2022 - 2023	-0.0037	0.0184	0.0053	-0.0154	0.0079	-0.7052	11	0.4953

Analysis of the Mechanism of TFP Enhancement by NQP

Building on the factor-level decomposition of TFP and the quantification of single-factor productivity, this section investigates the mechanisms through which NQP promotes TFP growth. Recognising that NQP is defined by disruptive technological innovations, the innovative reallocation of production factors, and profound industrial transformation and upgrading, the subsequent analysis examines these three dimensions individually.

Innovative Allocation of Production Factors

The findings indicate a unidirectional relationship between communication and information: information resources are activated through communication capacity. The most substantial productivity gains, particularly in labour and land, occur when information structures are mediated by advanced communication systems, reflecting a digital restructuring of traditional contributions rather than mere accumulation (Castells, 2010; Shannon and Weaver, 1949). This observation aligns with evidence that ICT-enabled communication complements information resources to enhance organisational and economic performance (Brynjolfsson and Hitt, 2000; Jorgenson and Stiroh, 2000), and supports the notion of ICT as a general-purpose technology whose impact manifests through the complementary reconfiguration of other inputs (Bresnahan and Trajtenberg, 1995).

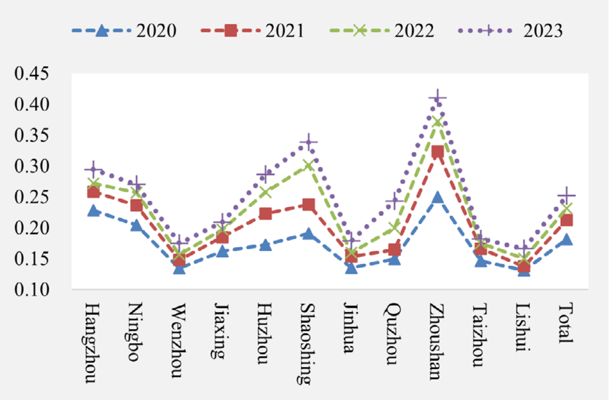

Figure 3: Labor Productivity by Region in Zhejiang Province, 2020–2023.

Departing from conventional factor combinations and growth pathways, the innovative reallocation of production factors has generated more efficient and qualitatively improved forms of productivity. Given the distinctive role of data as a production factor, its integration represents a break from traditional growth models. As discussed previously, the introduction of new factor types has modified the correlations among inputs, reflecting qualitative shifts in their structure and function. To further capture the efficiency and quality implications of this innovative allocation, annual variations in single-factor productivity are examined. Labour productivity, in particular, shows a marked upward trajectory. Year-on-year comparisons reveal consistent increases in both land and labour productivity throughout the observation period. The inclusion of new production factors has enhanced the intrinsic quality of traditional factors while promoting optimised allocation, thereby elevating overall productivity. Annual labour productivity trends are illustrated in Figure 3.

Conversely, data productivity exhibits a declining trend over the observation period, as shown in Figure 4. This reduction may result from diminishing marginal returns and the persistence of data silos, which constrain effective utilisation despite the disruptive potential of data. Additionally, the process of data factorisation remains underdeveloped, and market valuation fails to capture the true economic contribution of data. Specifically, the market price of data is lower than its marginal output, while the rapid expansion of data input further diminishes marginal returns. Capital productivity, unlike other single-factor measures, does not display a consistent annual trend across regions during the observation period. A plausible explanation is that capital stocks are more adjustable over time than other factors, and their spatial allocation is generally more flexible and efficient.

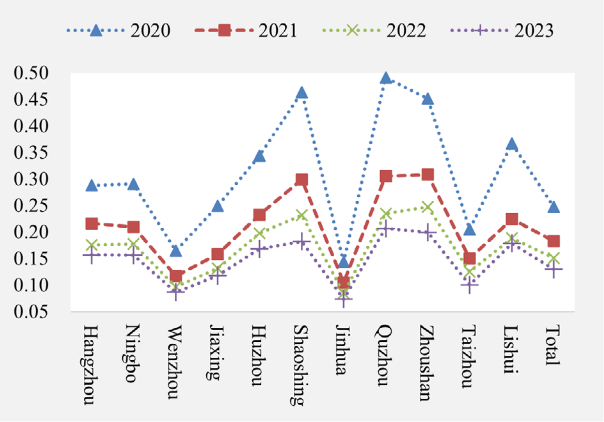

Figure 4: Data productivity by region in Zhejiang Province, 2020–2023.

To statistically evaluate interannual productivity variations, paired-sample t-tests are applied to compare mean TFP and single-factor productivity values across years. The analysis focuses on year-to-year differences in productivity across 11 regions and the province as a whole, yielding a total sample size of 12. For each productivity type, two comparisons are made over the four-year period, resulting in six t-test analyses.

Comparison of annual averages indicates that TFP did not exhibit an upward trend during the observation period, as presented in Table 6. Relative to 2020, TFP in subsequent years declined significantly, though no significant differences were detected between other years at the 5% significance level. This underscores the ongoing debate over using core markers for TFP measurement.

Table 7: Results of Paired-Sample t-Tests for Land Productivity (2020–2023).

Land Productivity	Mean	Std.Dev.	Std.Error	95% CI (Lower)	95% CI (Upper)	t-value	df	p-value
2020 - 2021	-0.0119	0.0102	0.0029	-0.0184	-0.0054	-4.0409	11	0.0019
2020 - 2022	-0.0239	0.0227	0.0066	-0.0384	-0.0095	-3.6427	11	0.0039
2020 - 2023	-0.0367	0.0311	0.0090	-0.0565	-0.0170	-4.0918	11	0.0018
2021 - 2022	-0.0120	0.0140	0.0040	-0.0209	-0.0031	-2.9716	11	0.0127
2021 - 2023	-0.0248	0.0234	0.0068	-0.0397	-0.0100	-3.6771	11	0.0036
2022 - 2023	-0.0128	0.0114	0.0033	-0.0201	-0.0056	-3.9031	11	0.0025

Table 8: Results of Paired-Sample t-Tests for Labor Productivity (2020–2023).

Labor Productivity	Mean	Std.Dev.	Std.Error	95% CI (Lower)	95% CI (Upper)	t-value	df	p-value
2020 - 2021	-0.0302	0.0191	0.0055	-0.0423	-0.0181	-5.4831	11	0.0002
2020 - 2022	-0.0538	0.0347	0.0100	-0.0758	-0.0318	-5.3758	11	0.0002
2020 - 2023	-0.0769	0.0434	0.0125	-0.1045	-0.0493	-6.1353	11	0.0001
2021 - 2022	-0.0236	0.0182	0.0053	-0.0352	-0.0120	-4.4932	11	0.0009
2021 - 2023	-0.0467	0.0282	0.0081	-0.0646	-0.0288	-5.7395	11	0.0001
2022 - 2023	-0.0231	0.0113	0.0033	-0.0303	-0.0159	-7.0723	11	0.0000

Table 9: Results of Paired-Sample t-Tests for Capital Productivity (2020–2023).

Capital Productivity	Mean	Std.Dev.	Std.Error	95%CI(Lower)	95%CI(Upper)	t-value	df	p-value
2020-2021	-0.0069	0.0135	0.0039	-0.0155	0.0017	-1.7682	11	0.1047
2020-2022	0.0077	0.0208	0.0060	-0.0055	0.0209	1.2806	11	0.2267
2020-2023	0.0163	0.0300	0.0086	-0.0028	0.0353	1.8799	11	0.0869
2021-2022	0.0146	0.0145	0.0042	0.0054	0.0238	3.4869	11	0.0051
2021-2023	0.0232	0.0243	0.0070	0.0077	0.0386	3.3001	11	0.0071
2022-2023	0.0086	0.0127	0.0037	0.0005	0.0166	2.3485	11	0.0386

Table 10: Results of Paired-Sample t-Tests for Data Productivity (2020–2023).

Data Productivity	Mean	Std.Dev.	Std.Error	95% CI (Lower)	95% CI (Upper)	t-value	df	p-value
2020 - 2021	0.0999	0.0488	0.0141	0.0688	0.1309	7.0834	11	0.0000
2020 - 2022	0.1388	0.0650	0.0188	0.0974	0.1801	7.3910	11	0.0000
2020 - 2023	0.1623	0.0746	0.0215	0.1150	0.2097	7.5400	11	0.0000
2021 - 2022	0.0389	0.0176	0.0051	0.0277	0.0501	7.6417	11	0.0000
2021 - 2023	0.0625	0.0293	0.0085	0.0438	0.0811	7.3794	11	0.0000
2022 - 2023	0.0236	0.0135	0.0039	0.0150	0.0321	6.0727	11	0.0001

Table 11: Correlation between the Application of Communication Technology, Digital Transformation, and Factor Equities in Zhejiang Province, 2020–2023.

Indicator		Land Equity	Labor Equity	Capital Equity	Data Equity
Number of computers in use at the end of the period	Pearson correlation	0.8323	0.9453	0.9073	0.8594
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44
Number of firms with websites	Pearson correlation	0.9125	0.9416	0.9240	0.8579
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44
Number of firms with e-commerce transaction activities	Pearson correlation	0.8716	0.9539	0.9397	0.8284
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44
E-commerce sales	Pearson correlation	0.7309	0.9057	0.8444	0.7799
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44
E-commerce purchases	Pearson correlation	0.6990	0.8590	0.8692	0.7528
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44

Note: Full data for these indicators is presented in the original dataset for detailed analysis.

In contrast, land and labour productivity demonstrated statistically significant year-on-year improvements at the 5% level, as shown in Tables 7 and 8, respectively. Capital productivity exhibited no significant difference relative to 2020 on average (Table 9); however, a notable decline is observed between 2021 and 2023, with a year-on-year downward trend. Regional performance varies: in Ningbo, Jinhua, and Taizhou, capital productivity initially rises before declining, whereas in Wenzhou, Huzhou, and Lishui it declines consistently. In contrast, Jiaxing records a continuous increase throughout the observation period. Unlike land and labour productivity, data productivity's mean value declined steadily over the observation period, as reported in Table 10. Figure 4 highlights that this downward trend is consistent across the province, mirroring the trajectory observed in TFP during the same period.

Deep Transformation and Upgrading of Industries

NQP is fundamentally supported by strategic emerging and future industries, which are instrumental in driving TFP growth. Recognising that industrial digitisation constitutes a critical channel for deep industrial transformation and upgrading in the digital era, this section examines the association between industrial digitisation and single-factor productivity using correlation analysis. Five key indicators are employed to capture the deployment of ICT and digital transformation within each region: (1) the number of computers in active use at the end of the period, (2) the number of enterprise-owned websites, (3) the number of enterprises participating in e-commerce transactions, (4) e-commerce sales volume, and (5) e-commerce purchase volume. Data for these indicators were sourced from the Zhejiang Statistical Yearbook. Given that these variables represent absolute values, factor equity is applied to quantify factor productivity. The processed results, analysed using SPSS, are presented in Table 11. The correlation analysis demonstrates that both groups of selected indicators exhibit statistically significant linear relationships at a significance level below 0.001. The strongest correlation occurs between the number of enterprises engaged in e-commerce transactions and labour factor equity, with a correlation coefficient of 0.9539. This finding indicates substantial industrial transformation driven by digitalisation, which positively influences the enhancement of overall TFP.

Table 12: Correlation between Innovation Indicators and Factor Equities in Zhejiang Province, 2020–2023.

Indicators		Land Equity	Labor Equity	Capital Equity	Data Equity
R&D expenditure	Pearson Relevance	0.8796	0.9756	0.9019	0.8423
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44
Patent authorization	Pearson correlation	0.7928	0.8928	0.9670	0.8113
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44
Inventions	Pearson Relevance	0.7001	0.8846	0.8514	0.7427
	Significance (two-side)	0.0000	0.0000	0.0000	0.0000
	N	44	44	44	44

Note: Full data for these indicators is presented in the original dataset for detailed analysis.

Technological Revolutionary Breakthrough

NQP represents a sophisticated form of productivity in which innovation functions as the primary driving force. To capture the regional variation in R&D intensity and innovation capability, three indicators are employed: R&D expenditure, patent grants, and the number of inventions. The corresponding data are sourced from the Zhejiang Statistical Yearbook for the relevant years. The relationship between these R&D indicators and single-factor productivity is examined. As the R&D indicators are expressed in absolute terms, factor equities are used as proxies for single-factor productivity to maintain analytical consistency. The correlation results, computed via SPSS, are presented in Table 12. The analysis reveals that all R&D indicators and factor equities display statistically significant linear relationships at a significance level below 0.001. The strongest correlation is observed between R&D expenditure and labour factor equity, with a coefficient of 0.9756, underscoring the positive impact of innovation on TFP.

Table 13: Stepwise Regression Results for Labor Factor Equity across Regions in Zhejiang Province (2020–2023).

Parameter	Coefficient	Standard Error	t-value	p-value
Intercept	-1.8919	13.9844	-0.1353	0.8931
R&D Expenditure	2.2623	0.2236	10.1177	0.0000
Number of Computers in Use at End of Period	-0.0009	0.0001	-6.6534	0.0000
E-commerce Sales	0.0614	0.0134	4.5709	0.0001
Number of Firms with E-commerce Trading Activities	0.1079	0.0277	3.8928	0.0004
Equity in Data Elements	0.1920	0.0675	2.8441	0.0071

Considering that labour productivity or labour factor equity is a central metric in evaluating NQP, a regression model is constructed to examine the systematic effects of production factor allocation, industrial upgrading, and technological advancement. Explanatory variables include ICT adoption, digital transformation, R&D indicators, and other factor-related measures. To address the potential for multicollinearity among the numerous explanatory variables, a stepwise regression method is applied with a significance threshold of 0.05. The final model retains five explanatory variables, producing a coefficient of determination (R^2) of 0.9789 and an F-statistic of 352.5155. The estimated parameters are reported in Table 13.

The results indicate that R&D expenditure, data factor equity, and e-commerce-related variables collectively account for the variation in labour factor equity. Data factors, in particular, act as enablers of labour productivity, demonstrating that the innovative reallocation of production inputs can substantially improve labour efficiency. The growth of the digital economy provides a concrete pathway for enhancing TFP. Interestingly, the number of computers in active use at the end of the period exhibits a negative effect on labour factor equity. This apparently counterintuitive outcome is likely due to multicollinearity, as correlation analysis shows strong positive associations between this variable and all other explanatory variables in the model, with correlation coefficients exceeding 0.8323. This suggests that the stepwise regression procedure did not entirely mitigate multicollinearity, potentially distorting individual parameter estimates.

Discussion and Conclusion

This study develops a comprehensive framework for measuring and decomposing TFP, integrating data elements through the lens of NQP theory. From an information-science standpoint, productivity is reconceptualized as the measurable performance arising from the interaction between information resources and communication infrastructures, which together generate economic value within an information ecosystem. The empirical analysis examines the effect of NQP on TFP across Zhejiang Province during 2022–2023. By combining DEA with the Shapley value cooperative game model, the study offers a detailed assessment of TFP within a multifactor context, without presuming any functional form for production, and enables decomposition of the marginal contributions of each factor type.

The findings indicate that TFP across all regions remained relatively stable during the study period, with technological progress being limited. This suggests that NQP is still in its formative and accumulation stages. Data factors—a core element of NQP—demonstrated substantial influence in enhancing TFP, particularly in regions where data productivity was relatively strong; however, overall trends exhibited diminishing marginal returns. At the same time, productivity of traditional inputs such as land and labor increased considerably, illustrating a qualitative transformation of conventional factor allocation models facilitated by data and technology. This effect exemplifies the "factor reorganization" phenomenon central to NQP. Additionally, industrial digitalisation and technological innovation were significant drivers of factor productivity, confirming the role of NQP at both the industrial and innovation-system levels.

These results highlight the synergistic operation of information-type and communication-type variables: only when organizational capabilities for storing, governing, and analysing information (the information dimension) are paired with effective digital communication networks (the communication dimension) do tangible productivity gains emerge. This interaction resonates with classical information-flow theory (Shannon and Weaver, 1949) and reinforces the notion that productivity in digital economies depends not solely on technology inputs, but on the form, quality, and operationalisation of information flows. Through systematic modelling and empirical analysis, this study not only validates the utility of TFP as a key indicator of NQP but also provides a practical framework for evaluating production efficiency under complex factor systems. The findings offer actionable guidance for local policymakers to optimise factor allocation, enhance utilisation of digital resources, and accelerate industrial digitalisation and R&D-led innovation. From an information-science perspective, these results suggest that data governance and communication efficiency jointly constitute the productive forces that underpin digital economies.

Empirical evidence demonstrates that TFP in the digital era emerges from the orchestration of information and communication capabilities. The information dimension encompasses the economy's data intelligence, information resources, and analytical capacities (Borgman, 2015; Buckland, 1991), while ICT and digital platforms coordinate and operationalise these resources through communication networks (Castells, 2010; Shannon and Weaver, 1949). Recognising these as distinct production inputs transforms TFP from a residual outcome of technological deployment into a measurable product of the information-communication system. Consequently, policy emphasis should target the enhancement of communication capacities to convert existing information resources into tangible productivity gains (Brynjolfsson and Hitt, 2000; Jorgenson and Stiroh, 2000). The dual-factor analysis reveals a systemic interdependence: productivity gains materialise when information resources (data and analytic power) are effectively mobilised through mature communication networks (ICT infrastructure, digital platforms) (Castells, 2010; Shannon and Weaver, 1949). This mirrors information-flow principles in library and information science, where data remain latent until effectively disseminated, and productivity manifests through the transformation of information potential into realised output (Davenport, 1998; Star and Ruhleder, 1996).

By defining information-type and communication-type inputs as primary predictors of TFP, this paper bridges the gap between information science and productivity theory. Rather than conceptualising TFP as a by-product of exogenous technology, it is framed as the direct result of interactions between information systems and communication networks (Borgman, 2015; Castells, 2010). This perspective operationalises the analysis of data governance, ICT connectivity, and knowledge sharing as joint contributors to national productivity and innovation, consistent with the view of ICT as a general-purpose technology whose benefits arise from complementary organisational reconfiguration (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Hitt, 2000).

Nonetheless, the study has several limitations and avenues for further research. First, constrained by data availability and the two-year timeframe (2020–2023), the analysis cannot fully capture long-term dynamic effects of NQP on TFP. Longer-term tracking would provide stronger insights into cumulative impacts. Second, although data elements are included, the indicator system is predominantly focused on Internet infrastructure, omitting dimensions such as algorithmic capacity, data quality, and data openness. Future work should broaden these dimensions and incorporate heterogeneous data sources. Moreover, while DEA combined with the Shapley model enables interpretable and equitable factor decomposition, it remains static and cannot fully describe the evolutionary dynamics and diffusion of NQP. Future studies could integrate dynamic DEA, multi-stage production frontiers, or complex system simulations to capture interactions among data, institutional frameworks, and innovation factors. At the policy level, more attention is needed to mechanisms for data authentication and circulation, optimisation of digital infrastructure, and the translation of technological advances into measurable economic outcomes.

Overall, the study demonstrates that NQP is realised through the coordination of information resources and communication infrastructures within an institutional system of data governance, interoperability, and knowledge sharing. Strengthening these linkages transforms TFP into a diagnostic indicator of information-system maturity and communication efficiency, both foundational to sustainable digital transformation. In summary, the digital era generates productivity through the orchestrated interaction of information and communication capabilities, rather than isolated technological deployment. This aligns with information-ecosystem theory, where the utility of information is determined by its situational circulation, availability, and governance. Accordingly, NQP reflects operational maturity in information infrastructure rather than mere technological sophistication.

Policy implications include delineating complementary domains: (i) information-resource management, encompassing data quality, metadata standards, and governance, and (ii) communication-infrastructure development, emphasising interoperability and connectivity. Strengthening metadata standards and protocols facilitates higher-quality, reusable information (Borgman, 2015; Davenport, 1998), while expanded ICT coverage and platform interoperability ensures effective dissemination of information (Castells, 2010; Star and Ruhleder, 1996). When harmonised, these measures create an integrated information ecosystem, enabling the co-existence of information resources and communication capacity to generate measurable productivity gains (Brynjolfsson and Hitt, 2000; Jorgenson and Stiroh, 2000; Shannon and Weaver, 1949).

By operationalising NQP as information-communication efficiency within a DEA-Shapley framework, this study confirms that productivity emerges from systematic interactions between information resources and communication infrastructures. Policies supporting metadata standardisation, data openness, and interoperable platforms are critical for measurable productivity enhancement. Future research should extend this work by dynamically modelling information flows, assessing institutional readiness, and examining how knowledge infrastructures can evolve into self-reinforcing engines of innovation and productivity. This positions TFP as a pragmatic measure of information-system maturity, translating information-science theory into quantifiable digital-productivity outcomes.

Consent for Publication

All authors have provided their consent for publication of this study. There are no identifiable individuals or personal data included in this manuscript, ensuring compliance with publication ethics.

Competing Interests

The authors declare that they have no competing interests.

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