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Exploring Pathways for the Green and Digital Transformation of the Three Elements of Productive Forces Driven by New-Quality Productive Forces

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Abstract: Artificial intelligence, big data, cloud computing, and related technologies are increasingly embedded in production, while green and low-carbon development imposes stricter requirements on resource use and technological application. This study employs a qualitative, literature-based conceptual method to distinguish factors of production from the three elements of productive forces and to clarify the position of data within the productive-force system. It develops an integrated framework for examining how new-quality productive forces promote the green and digital transformation of workers, means of labor, and objects of labor. The analysis identifies four interconnected pathways: strengthening workers' green digital literacy, incorporating ecological objectives into intelligent means of labor, supporting precise and circular resource governance through digital technologies, and coordinating the three elements through data governance. Sustainable productivity gains depend on the joint integration of human agency, technical efficiency, data responsibility, and ecological limits into production decisions.

Keywords: New-quality Productive Forces; Three Elements of Productive Forces; Data as a Factor of Production; Green Digital Transformation; Data Governance.

1. Introduction

Artificial intelligence, big data, cloud computing, digital twins, and related technologies have become increasingly embedded in production processes, strengthening real-time perception, networked coordination, and data-supported decision-making. Concurrently, resource and environmental constraints are tightening. China's dual-carbon targets and comprehensive green transformation policy require production systems to reduce resource consumption, control emissions, and improve ecological efficiency[1]. New-quality productive forces, driven by scientific and technological innovation, provide a useful framework for examining this transition because their formation involves the coordinated upgrading of workers, means of labor, objects of labor, and their modes of combination[2-4].

Digitalization carries material and environmental costs. Data centers, communication networks, intelligent equipment, and algorithmic systems consume electricity, materials, and computing resources throughout their life cycles. Efficiency gains may also stimulate additional demand, wider system deployment, and production expansion. Research on information and communication technologies indicates that improvements in unit-level efficiency can coexist with growth in aggregate energy demand through direct, indirect, and economy-wide rebound effects[5]. Green digital transformation therefore requires production objectives, technical systems, workforce capabilities, resource allocation, and governance arrangements to be aligned with ecological constraints.

Current scholarship provides four principal foundations for this analysis. Marxist productive-force theory defines workers, means of labor, and objects of labor as the basic elements through which society transforms nature and produces material conditions[6]. Research on data-driven innovation explains how data can reduce information costs, improve coordination, and support knowledge creation[7]. Studies of Industry 4.0 identify opportunities for resource optimization, intelligent monitoring, flexible production, and improved energy management[8]. Research on green and digital skills, trustworthy artificial intelligence, circular production, and data governance further emphasizes workforce capability, human oversight, life-cycle coordination, institutional safeguards, and responsible data use[9][14]-[14].

Despite these contributions, the literature remains fragmented across technological, organizational, labor, resource, and institutional perspectives. The distinction between factors of production and the three elements of productive forces also requires greater precision, particularly when data is incorporated into the analytical framework. In addition, technical efficiency often receives more attention than worker agency, total-resource constraints, rebound effects, and the environmental costs of digital infrastructure. A unified account is therefore needed to explain the coordinated transformation of workers, means of labor, objects of labor, and data.

This study addresses these issues through a qualitative, literature-based conceptual analysis. The analysis proceeds in three stages: it clarifies the relevant conceptual categories and the functional position of data; it examines the effects of digitalization and greening on each element of productive forces; and it develops a coordination mechanism linking human agency, technical systems, data governance, resource constraints, and ecological objectives. The study identifies analytical relationships and practical pathways and does not test causal effects with a specific dataset.

The paper contributes an integrated framework for the green and digital transformation of the three elements of productive forces. Data is conceptualized as a factor that enters production through embedding and empowerment. The framework connects workers' green digital literacy, the life-

cycle governance of intelligent means of labor, the precise and circular management of material resources, and a data-supported coordination mechanism. Section 2 presents the conceptual framework; Sections 3-6 analyze the transformation pathways; Section 7 discusses their implications; and Section 8 concludes the study.

2. Conceptual Distinctions and Analytical Framework

2.1. Defining New-Quality Productive Forces and Its Analytical Boundaries

New-quality productive forces is a concept developed in China's contemporary political economy to describe an advanced form of productivity generated by revolutionary technological breakthroughs, innovative allocation of production factors, profound industrial transformation, and the upgrading and optimal combination of workers, means of labor, and objects of labor. Its defining features are innovation, high technology, high performance, high quality, consistency with the new development philosophy, and a substantial increase in total factor productivity[2-4]. In this paper, the term does not refer to every increase in output, every use of digital technology, or the simple expansion of capital investment. Its analytical boundary is a qualitative reconfiguration of productive capacity that changes the content and combination of the three elements of productive forces and supports high-quality, green, and resilient development.

The concept overlaps with, but is not identical to, several established terms in international economics and development studies. Productivity growth describes changes in output relative to inputs, while technological progress refers to shifts in the production frontier and is one source of such growth[15]. Innovation-driven development is broader than a single productivity measure and concerns the institutions, capabilities, and policies through which knowledge is converted into new products, processes, organizations, and social value[16]. New-quality productive forces incorporates these mechanisms but places greater emphasis on their systemic embodiment in workers, means of labor, objects of labor, industrial organization, and production relations. The term is therefore used here as a context-specific, meso-to-system-level framework rather than as a universal substitute for productivity, technological progress, or innovation-led growth.

2.2. Factors of Production and the Three Elements of Productive Forces

Factors of production and elements of productive forces occupy related yet distinct analytical levels. Economic analysis treats labor, land, capital, technology, and data as inputs involved in allocation and value creation. Marxist productive-force theory examines society's practical capacity to transform nature and produce material conditions. Within this framework, workers constitute the active subjects of production, means of labor mediate productive activity, and objects of labor comprise the natural or processed materials upon which labor acts [6].

The two categories therefore perform different explanatory functions. Labor becomes an effective productive force through workers' knowledge, skills, health, and practical judgment. Capital and technology operate through machinery, industrial software, sensors, platforms, and algorithmic systems, while land, energy, minerals, and raw materials become concrete objects of labor within specific production processes. This paper accordingly focuses on the green and digital transformation of the three elements of productive forces.

2.3. Data as a Factor of Production

The status of data in production is contested. One strand of research treats data as a distinct intangible asset or factor input because it is storable, reusable, combinable, and largely nonrival, so the same dataset may support multiple productive and innovative uses[7][17][18]. Another strand emphasizes that raw data has no stable productive value on its own: value arises only when data is combined with algorithms, computing infrastructure, domain knowledge, organizational routines, legitimate access, and user trust. From this perspective, data is primarily a complementary or enabling resource that improves the effectiveness of established factors rather than an autonomous source of productivity[14][18].

This paper adopts a qualified factor-of-production position. Data is treated as a factor because it can be deliberately collected, governed, combined, reused, and allocated as an input to production and innovation. However, it is not placed alongside workers, means of labor, and objects of labor as a fourth basic element of productive forces. Its productive effect is relational and conditional: workers use data to strengthen cognition and decision-making; databases, platforms, algorithms, and computing infrastructure become components of digital means of labor; and raw, operational, or environmental data may become objects of processing and analysis. This position makes data governance a coordination mechanism within the framework and avoids attributing productive agency to data independently of human, technical, institutional, and ecological conditions.

2.4. Digitalization-Greening-Three-Element Synergy

Digitalization provides real-time sensing, intelligent analysis, prediction, and dynamic optimization, while greening establishes criteria concerning resource conservation, low-carbon development, pollution prevention, and ecological protection. Sustainable transformation emerges when these capabilities and constraints are incorporated into the coordinated upgrading of workers, means of labor, and objects of labor [2-4] [8]. Data links the three elements through a feedback process in which workers interpret information, technical systems adjust operations, and resource conditions reshape decisions and parameters.

3. Reshaping Workers' Core Competencies: Green Digital Literacy

New-quality productive forces require workers to participate in digital diagnosis, optimization, and innovation. In this study, green digital literacy is defined as a work-oriented capability that integrates five dimensions: information, data, and artificial-intelligence literacy; smart-equipment operation and digital problem-solving; environmental systems and life-cycle literacy; critical, ethical, and risk-aware judgment; and collaboration, participation, and continuous learning. Together, these dimensions enable workers to interpret production data, understand the limits of model outputs, identify abnormal conditions, combine digital

evidence with practical experience, and evaluate energy use, material loss, emissions, equipment life, safety, and circularity [9-11].

Assessment should emphasize observable performance rather than self-reported familiarity alone. Operational indicators may include the ability to verify data quality, explain a dashboard or model recommendation, diagnose anomalies, estimate uncertainty, calculate energy and material intensity, identify carbon and pollution hotspots, compare life-cycle trade-offs, apply maintenance and circular-production procedures, document automated decisions, and intervene safely when system outputs conflict with on-site conditions. Indicators should be adapted to occupational roles and assessed through scenario-based tasks, simulations, work samples, and longitudinal workplace records.

Cultivation requires a combination of formal education and workplace learning. Vocational education and enterprise training should integrate data analysis, smart-equipment operation, energy management, carbon accounting, circular production, cybersecurity, and responsible artificial-intelligence use. Role-specific competency matrices can connect training modules to production tasks, while digital twins, supervised simulations, cross-functional improvement projects, mentoring, and micro-credentials can support repeated practice and recognition. Training content should be updated with changes in equipment, regulation, and environmental targets.

Worker participation is equally important to the governance of intelligent production. Appropriate involvement in indicator setting, technical testing, risk identification, and performance evaluation can preserve practical judgment and improve organizational learning. Principles of trustworthy artificial intelligence emphasize human-centered values, transparency, robustness, accountability, and effective human oversight [12]. Applied to production, these principles support systems that expand workers' capabilities and maintain clear channels for intervention and responsibility.

4. Reconstructing the Technological Logic of the Means of Labor

In the digital era, means of labor encompass smart equipment, sensors, industrial software, algorithmic models, data platforms, and computing infrastructure. These systems support real-time monitoring, predictive maintenance, production scheduling, and process optimization. Their environmental performance depends on life-cycle design and operation. Energy efficiency, material use, repairability, compatibility, service life, load forecasting, preventive maintenance, and model-size matching should be incorporated into technical management. Evaluation should consider carbon intensity, resource-use efficiency, equipment life, and pollution risk alongside output, cost, speed, and accuracy [5-8].

Technical systems also require transparency, explainability, robustness, and accessible forms of human intervention [12]. A practical governance cycle can connect system perception, worker judgment, parameter adjustment, and result feedback. When model outputs conflict with on-site experience, organizations should verify data quality, conduct limited trials, monitor consequences, and allocate responsibilities among developers, managers, maintainers, and frontline workers. Such arrangements enable means of labor to balance economic performance, ecological performance, and human development.

5. Transforming the Governance of Objects of Labor

Objects of labor include land, minerals, energy, raw materials, intermediate products, and other material resources entering production. Digital technologies can represent and trace their stocks, flows, quality, location, and environmental impacts. Order, inventory, and supplier data support more accurate procurement; equipment and energy data improve load adjustment and waste reduction; and product life-cycle information facilitates maintenance, reuse, remanufacturing, and recycling. These applications provide the informational basis for precise and circular resource governance [13].

Efficiency improvements require evaluation at both unit and aggregate levels. Lower unit costs and faster services can stimulate additional demand, production expansion, and more frequent logistics or digital activity. Resource governance should therefore combine efficiency indicators with total-resource controls, environmental carrying capacity, and long-term ecological thresholds [5]. This approach directs digital tools toward absolute resource conservation and sustained ecological performance.

6. Coordinating the Three Elements through Data Governance

Data connects workers, means of labor, and objects of labor, while its collection, storage, transmission, and computation entail organizational, legal, technical, and material costs. Effective governance combines access and reuse with quality, security, accountability, proportionality, and clearly defined purposes [7][14][18]. Organizations should avoid repeated collection of low-value data, classify data according to use and sensitivity, manage storage by access frequency, remove obsolete data, and align model complexity and computing capacity with actual tasks.

A green data-evaluation mechanism should account for energy use, carbon emissions, equipment depreciation, resource savings, safety benefits, and public value. Responsibilities also need to be allocated among enterprises, government agencies, research institutions, technology providers, managers, and workers. Institutional safeguards for data creation, sharing, protection, and public-interest use provide the basis for coordinated action [14]. Combined with human-centered artificial-intelligence governance, these arrangements create a feedback system in which workers interpret data, technical systems respond to resource conditions, and changes in objects of labor inform subsequent decisions.

7. Discussion

The proposed framework highlights the socio-technical character of green digital transformation. Equipment investment can improve short-term efficiency, yet durable gains also depend on workforce capability, institutional capacity, and ecological governance. Data should be assessed through the productive and public value it creates in relation to its economic and environmental costs. Ecological constraints should therefore be incorporated into the objectives and evaluation criteria of digital production systems so that improvements in efficiency contribute to

reductions in aggregate resource pressure.

In theoretical terms, the framework differs from technology-centred Industry 4.0 approaches by treating worker agency, data responsibility, and ecological limits as coequal design requirements rather than as secondary conditions of technical adoption. It also extends classic socio-technical systems thinking: joint optimization is applied not only to people and technology, but also to the material and energy metabolism of production and to the institutions governing data. Compared with circular-economy frameworks, which emphasize product life extension and closed material loops, the present framework specifies how workers, intelligent means of labor, and data-based feedback convert traceability into maintenance, reuse, remanufacturing, and recycling decisions. Compared with data-governance approaches, it adds the environmental costs of collection, storage, transmission, and computation to questions of access, security, rights, and accountability [8],[13],[14],[19].

The analysis also rejects both technological determinism and a simple additive view of production factors. Digital tools do not automatically produce green outcomes, because optimization objectives may prioritize speed, output, or cost while displacing environmental burdens elsewhere in the life cycle. Likewise, data is not assumed to generate value independently. Its contribution depends on complementary skills, infrastructure, organizational routines, and legitimate governance. The framework therefore predicts that transformation will be constrained by the weakest element: advanced equipment without worker capability can create underuse or unsafe automation; skilled workers without interoperable systems cannot act on information; and precise monitoring without aggregate resource limits can intensify rebound effects. Green and digital transformation should consequently be evaluated as a coordinated system outcome rather than as the sum of isolated technology projects.

Several limitations delimit the framework. First, it is a conceptual synthesis and does not establish causal effects or estimate the relative contribution of each pathway. Second, the concept of new-quality productive forces is rooted in China's political-economic and policy context; its application outside that context requires careful translation into local institutions, industrial structures, and development priorities. Third, the framework is most directly applicable to production-oriented sectors and gives less attention to household consumption, finance, and macroeconomic demand. Fourth, it assumes a minimum level of organizational and regulatory capacity for data governance, worker participation, and life-cycle measurement, conditions that may be absent in small firms or less-developed regions. Finally, several constructs, including green digital literacy, ecological performance of intelligent means of labor, and data-governance maturity, remain difficult to measure consistently across sectors.

Future research should convert the conceptual relationships into testable propositions and indicators. A multidimensional green digital literacy scale could combine scenario-based assessments, observed workplace performance, and self-reported confidence. Firm- or plant-level studies could examine whether worker participation moderates the effects of intelligent equipment on energy use, waste, safety, and productivity. Longitudinal and quasi-experimental designs could evaluate training programs, digital-retrofit subsidies, data-governance reforms, or circular-production pilots. Sectoral comparisons should test how energy intensity, material dependence, data sensitivity, and worker discretion alter the framework's mechanisms. Further work should also examine thresholds and unintended consequences, including rebound effects, unequal access to skills, algorithmic work intensification, and the transfer of environmental burdens across supply chains. Mixed-method studies can clarify why technically similar systems generate different outcomes in different organizational settings.

The policy and practical implications are correspondingly integrated. Public policy should avoid treating equipment investment as a sufficient proxy for transformation and should coordinate industrial, education, climate, labor, and data policies. Support programs can require life-cycle carbon assessment, repairability, interoperability, cybersecurity, and worker-training plans alongside productivity targets. Vocational institutions and enterprises should build role-specific competency matrices and provide modular, work-based training that combines data analysis, smart-equipment operation, carbon accounting, circular-production practices, and human oversight. Enterprises should adopt data minimization, proportional computing, clear responsibility allocation, and worker participation in indicator design and system testing. Pilot projects should report both unit efficiency and aggregate resource outcomes, allowing policymakers to distinguish genuine absolute reductions from apparent gains offset by expansion. Because sectoral and regional conditions differ, implementation should be staged, evidence-based, and adapted to local resource endowments and institutional capacity.

8. Conclusion

New-quality productive forces promote green digital transformation through the coordinated upgrading of workers, means of labor, objects of labor, and their modes of combination. Workers require green digital literacy and meaningful participation in technical decisions. Means of labor require ecological objectives, life-cycle management, and effective human oversight. Objects of labor require traceable, precise, and circular governance. Data functions as a factor that connects and empowers the three elements through appropriate institutions and technical arrangements.

Successful transformation depends on the joint incorporation of human development, technological efficiency, data responsibility, and ecological boundaries into production decisions. Such coordination can convert digital innovation into green, low-carbon, resilient, and high-quality productive capacity.

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