Beyond Traditional Manufacturing: Redefining Industrial Productivity Through Intelligent Process Optimisation, Digital Engineering, and Resource-Efficient Operations.

Abstract

Industrial productivity has long been measured as output per worker or per unit of combined inputs. That definition is becoming too narrow for factories in which quality losses, schedule instability, energy prices and material scarcity shape competitiveness as strongly as labour efficiency. This review examines how intelligent process optimisation, digital engineering and resource-efficient operations are redefining productivity in manufacturing. Following a systematic integrative design, the paper draws together a corpus of 30 journal studies from the 2020–2025 period. Two anchor studies frame the corpus: a review of zero-defect and zero-waste manufacturing through non-destructive inspection and an econometric study of digital transformation and total factor productivity. The material combines firm-level econometrics, reviews and design, modelling and experimental studies. The synthesis shows, first, that digital and intelligent technologies raise measured productivity, but only above thresholds of internal investment and external infrastructure, and largely through innovation, supply chain and human capital channels. Second, intelligent optimisation methods for defect prediction, root cause analysis, process mining and learning-based scheduling report substantial gains in quality, cycle time and responsiveness, yet most evidence comes from simulations or single cases. Third, digital engineering through virtual commissioning, simulation-based optimisation and model-driven digital twins shortens the path from design to stable operation, provided models are built at the right fidelity. Fourth, energy-aware scheduling and material reuse show that resource use can be optimised alongside time and cost. The paper proposes a redefined productivity framework with six dimensions and a layered capability architecture, and sets out an agenda for research.

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1. Introduction

Productivity is the measure by which manufacturing has traditionally judged itself. Labour productivity, the output produced per worker or hour, and total factor productivity, the output

that cannot be explained by measured inputs, remain central to economic analysis and managerial reporting. Both treat the factory as a transformation of inputs into outputs. What they capture less well are the losses that occur inside that transformation: defective parts that consume material and energy before being scrapped, schedules that collapse when a machine fails, electricity bought at peak prices, and components discarded when they could have been reshaped and reused.

Three developments are making those losses more visible and more controllable. Intelligent process optimisation applies machine learning, process mining and reinforcement learning to quality control and scheduling. Digital engineering uses simulation, virtual commissioning and digital twins to design, test and operate production systems before and during physical operation. Resource-efficient operations bring energy and material use into production decisions rather than treating them as fixed overheads. Together, they suggest that the productivity of a modern factory should be judged not only by how much it produces per input but by how much good output it delivers per unit of time, energy, material and capital, and how reliably it does so when conditions change.

The literature on each development is large but fragmented. Econometric studies estimate the productivity effects of digitalisation at firm level but say little about the engineering mechanisms involved (Wu et al., 2025). Engineering studies report impressive gains from specific algorithms and models but rarely connect them to firm performance or to resource use. Reviews of quality management argue that new paradigms such as zero-defect manufacturing must incorporate emerging technologies, but they are only beginning to align conceptual frameworks with empirical results (Psarommatis & Azamfirei, 2024).

This review brings these strands together. It asks how intelligent process optimisation, digital engineering and resource-efficient operations jointly redefine industrial productivity, what the evidence shows about their effects and limits, and how they can be integrated. The contribution lies in connecting firm-level productivity research with process- and system-level engineering evidence, in identifying the conditions that determine whether technical gains translate into productivity, and in proposing a multidimensional framework for measuring and managing productivity in technology-intensive manufacturing.

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After the research questions (Section 2) and review procedure (Section 3) are set out, Section 4 reviews firm-level evidence and measurement, Section 5 examines intelligent optimisation and digital engineering, and Section 6 addresses resource-efficient operations and presents the integrated framework. Section 7 discusses implications, research directions and limitations, and Section 8 offers closing observations.

2. Aim, Objectives and Research Questions

The purpose here is to establish how intelligent process optimisation, digital engineering and resource-efficient operations are changing what industrial productivity means and how it can be improved. Its objectives are to: (1) examine firm-level evidence on the productivity effects of digital and intelligent technologies and the conditions that shape them; (2) assess what intelligent optimisation and digital engineering methods contribute at process and system levels; (3) analyse how energy and material efficiency can be built into production decisions; and (4) synthesise these findings into a framework for defining and managing productivity.

Three research questions structure the analysis. RQ1 asks how firm-level studies characterise the productivity effects of digital and intelligent technologies, and what this implies for how productivity should be measured. RQ2 asks what intelligent process optimisation and digital engineering contribute to quality, time and system performance, and where their limitations lie. RQ3 asks how resource efficiency can be integrated into operational decision-making, and how the three approaches can be combined in a redefined productivity framework. Sections 4, 5 and 6 take up RQ1, RQ2 and RQ3 in turn.

3. Review Methodology

The review used a systematic integrative approach, chosen because the relevant evidence ranges from panel econometrics to algorithm design and laboratory experiments, which conventional meta-analysis cannot combine. An integrative design allows such studies to be read against each other while recording the type and strength of evidence each provides.

Searches were carried out in November 2026 in a large scholarly metadata index. Query strings combined productivity terms ("total factor productivity", "labour productivity", "performance measurement") with terms for intelligent optimisation ("zero defect manufacturing", "root cause analysis", "process mining", "reinforcement learning", "production scheduling"), digital

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engineering ("virtual commissioning", "digital twin", "simulation-based optimisation", "model engineering") and resource efficiency ("energy-aware scheduling", "renewable energy", "material efficiency", "component reuse").

Eligible records were peer-reviewed journal articles in English with a version of record dated 2020 to 2025 that addressed manufacturing and reported empirical, experimental or modelling results, or a systematic review, bearing on one or more of the research questions. Conference proceedings, editorials, articles outside the date range, and records whose abstracts could not be checked against their registered identifiers were excluded. Where several algorithmic studies addressed the same problem, preference was given to those reporting comparisons with established methods or real-world data.

The selection was anchored by two studies: a review of zero-defect and zero-waste manufacturing through non-destructive inspection technologies (Lario et al., 2025), and an econometric analysis of digital transformation and total factor productivity in listed manufacturing firms (Wu et al., 2025). The final corpus of 30 articles includes four econometric studies, one multiple case study, seven reviews and 18 design, modelling or experimental studies. This mix reflects the field: firm-level effects are estimated econometrically, while process- and system-level effects are mostly demonstrated through models, simulations and cases.

Each article was coded for its unit of analysis, method, technology, productivity dimension addressed, reported effect and stated limitations. The synthesis then compared findings within and across the three approaches and examined how they bear on the definition of productivity. Every quantitative result cited was taken from the source abstract or text, and no figures were derived or estimated independently.

4. Rethinking Productivity: Firm-Level Evidence and Measurement

Firm-level studies confirm that digital and intelligent technologies can raise productivity, but they also reveal conditions that the traditional productivity narrative overlooks. Using data on Chinese listed manufacturers from 2010 to 2022 and a text-based measure of digital transformation, one study found a significant positive effect on total factor productivity working through improved supply chain management, digital innovation and the allocation of human

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capital (Wu et al., 2025). The effect was stronger in exporting, state-owned, capital-intensive and non-high-tech firms, and stronger where intellectual property protection was robust. Crucially, gains materialised only once in-house spending on digital capability passed a certain floor and firms could draw on strong external digital infrastructure.

Infrastructure matters independently. Panel data on Chinese listed manufacturers between 2007 and 2020 showed that new-type infrastructure, which includes digital networks, significantly raised total factor productivity by encouraging innovation and improving the allocation of resources, with larger effects in larger, more innovative, externally competitive and mature firms (Wen & Zhan, 2023). Intelligent technology can also cushion productivity against external shocks. In a further study of listed manufacturers, labour productivity fell significantly under economic policy uncertainty, but the decline was mitigated in regions with high levels of industrial intelligence, particularly for high-technology and financially constrained firms, with human capital upgrading as a key channel (Li et al., 2023).

Labour productivity itself is less straightforward than it appears. Analysis of manufacturing in 27 European countries between 1995 and 2018 found a long-term relationship between personnel costs and apparent labour productivity, with personnel costs exerting a stronger influence than turnover. Rising personnel costs did not necessarily reduce profitability (Stundziene & Baliute, 2022). The finding cautions against treating labour cost reduction as the main route to productivity; investment in people and technology that raises the value of output per worker can be equally important.

Measurement systems lag behind technology. A multiple case study of small and medium-sized manufacturers reported that the maturity of manufacturing processes and the development of performance measurement and management were closely intertwined. Firms that had invested in their processes had also developed performance measurement, but performance management practices were less developed than measurement (Naeem & Garengo, 2022). In other words, firms may collect richer data without changing how they use it to manage.

These findings answer RQ1 in three parts. First, digital and intelligent technologies raise productivity on average, but through indirect channels, namely innovation, supply chain coordination and human capital, rather than through automation alone. Second, the gains depend on thresholds of internal investment, on external infrastructure and on institutional conditions,

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147 which explains why some firms experience a productivity paradox. Third, conventional
148 productivity measures capture outcomes but not the quality, time and resource losses that
149 technology addresses, and firms often lack management routines to act on new data. A redefined
150 productivity concept therefore needs to be multidimensional and linked to management practice.
151 Table 1 summarises the main productivity-related results reported in the corpus.

152 **Table 1. Selected productivity-related results reported in the corpus**

Study	Setting and method	Productivity dimension	Reported result
Wu et al. (2025)	Chinese listed manufacturers, 2010–2022; structural estimation	Total factor productivity	Positive effect above thresholds of internal digital investment and external infrastructure
Wen and Zhan (2023)	Chinese listed manufacturers, 2007–2020; panel data	Total factor productivity	New-type infrastructure raises productivity via innovation and resource allocation
Li et al. (2023)	Listed manufacturers, 2007–2019; regression	Labour productivity	Industrial intelligence mitigates losses from policy uncertainty
Stundziene and Baliute (2022)	27 European countries, 1995–2018; ARDL panel analysis	Labour productivity	Personnel costs linked to productivity; higher costs need not reduce profitability
Dogan and Areta Hiziroglu (2024)	Production cases; process control and process mining	Quality and time	Over 6% of processes out of limits; quality control activity drove cycle time
Yang and Xu (2022)	Reconfigurable flow line; deep reinforcement learning	Time and responsiveness	57.43% and 88.30% better than two meta-heuristics; decisions in 1.47 ms
Song et al. (2023)	Dynamic job shop; transformer-based learning	Time	13.84%–17.98% better than rules, genetic algorithms and other learning methods
Barbieri et al. (2021)	Flow shop; virtual commissioning of a digital twin	Capability and time	Reactive scheduling after breakdowns improved makespan
Karimi and Kwon (2021)	Optimisation models with solar and storage	Energy and cost	Energy cost cut by 23% alone and 36% combined; total cost by 7% and 15%
Ingarao et al. (2021)	Experimental reshaping of end-of-life aluminium	Material and energy	Reshaping outperformed recycling routes on energy and emissions

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154 ## 5. Intelligent Process Optimisation and Digital Engineering

155 Quality is where productivity losses are most direct, because every defect consumes inputs
156 without producing saleable output. Zero-defect manufacturing reframes quality management
157 around prediction and prevention. A comprehensive review argued that traditional quality

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paradigms were conceived before major technological advances and relied heavily on people's knowledge, and it proposed updated versions of the define-measure-analyse-improve-control cycle and statistical process control that exploit digital technologies fully (Psarommatis & Azamfirei, 2024). The anchor review of zero-defect and zero-waste manufacturing showed how non-destructive inspection, combined with sensors, robotics and artificial intelligence, enables in-line inspection that reduces material waste and energy use and lowers final factory cost (Lario et al., 2025).

Intelligent methods for finding the causes of defects are developing but remain under-used. A systematic review found that machine learning for root cause analysis in pursuit of zero defects was under-explored relative to the attention artificial intelligence receives in smart manufacturing (Papageorgiou et al., 2022). For low-volume, highly customised production, where historical data are scarce, a self-adaptive defect prediction model using the assembly complexity of process and design identified critical workstations whose defect rates deviated from prediction. Quality engineers could then target corrective action (Verna et al., 2023). People remain central: a review of 36 publications on human-centric zero-defect manufacturing found that managers cultivate a zero-defect culture, operators contribute through knowledge capture and feedback to engineers, and assistive technologies such as extended reality help eliminate human error. Barriers included high technology investment and resistance to changes in work tasks (Wan & Leirmo, 2023).

Process mining extends optimisation from individual operations to process flows. In production case studies, statistical process control found that more than 6% of processes exceeded specification limits, and process mining then revealed that prolonged quality control activity was the main factor lengthening cycle time; decision rules derived from the analysis indicated how to shorten unbalanced processes (Dogan & Areta Hiziroglu, 2024). On an automated testbed combining machining and logistics, a process mining framework analysed processes, time, resources and quality, identified bottlenecks and workload problems, and produced improvement proposals whose simulated implementation yielded significant productivity gains (Y. Lee et al., 2025). A hybrid process mining model that combined transition systems with statistical regression predicted remaining cycle times more accurately than alternatives on both artificial and real manufacturing logs (Choueiri et al., 2020).

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Scheduling is the second major arena for intelligent optimisation. A bibliometric review traced growing interest in reinforcement learning for production scheduling between 1996 and 2024 (Modrak et al., 2024). Reported gains are large in experimental settings. For a reconfigurable flow line with dynamic job arrivals, an advantage actor-critic approach outperformed iterated greedy and genetic algorithms by 57.43% and 88.30% in solution quality while using a small fraction of their computation time, and generated decisions within 1.47 milliseconds (Yang & Xu, 2022). A transformer-based deep reinforcement learning framework for dynamic job-shop scheduling, which used dispatching rules selected through data envelopment analysis as actions, delivered improvements of 15.98% over conventional dispatching rules, 17.98% over genetic algorithms and 13.84% over competing reinforcement learning approaches (Song et al., 2023).

Other studies confirm the pattern across settings. Deep reinforcement learning performed on a par with heuristic methods on automated lines with linear, parallel and re-entrant layouts, and it stayed stable when processing times were random (Shi et al., 2020). It outperformed dispatching rules in minimising weighted tardiness in injection mould production (S. Lee et al., 2020), and an improved approach for cloud manufacturing exceeded other learning-based methods in solution quality and generalisation by up to 32.8% and 28.6% (Wang et al., 2024). These results are encouraging, but they are almost all obtained on benchmark instances or simulated environments, and few studies report sustained performance in live production.

Digital engineering addresses a different productivity loss: the time and risk involved in bringing production systems into stable operation and keeping them there. Virtual commissioning connects real or emulated control systems to a simulation model of the plant so that control logic can be tested before physical commissioning. A comprehensive review found that it had been used mainly by large companies and had not become standard practice for smaller ones. It examined methods for reducing the effort of model creation and saw potential in cross-discipline, lifecycle-wide models that evolve into digital twins (Striffler & Voigt, 2023). A methodology based on virtual commissioning for integrating digital twins into existing manufacturing systems was validated in a flow shop, where the resulting architecture supported scheduling that reacted to machine breakdowns and improved makespan (Barbieri et al., 2021).

Model quality determines whether digital engineering pays off. From a model engineering perspective, some models are simply renamed digital twins, while others pursue exact replication

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and become needlessly complex; principles, metrics and an evolutionary concurrent modelling method were proposed to build twins of the right fidelity (L. Zhang et al., 2021). Because discrete-event simulation of complex systems is time-consuming, a multi-fidelity simulation-based optimisation method was developed for a digital twin of an aircraft parts workshop and outperformed other simulation-based optimisation methods on large-scale planning problems (Z. Zhang et al., 2022). At product level, a digital twin of composite assembly carried variation information from part design through manufacturing to assembly, accounting for the manufacturing signature left on part surfaces, and produced results consistent with experiments (Polini & Corrado, 2020).

In answer to RQ2, intelligent process optimisation contributes to productivity by preventing defects, exposing the causes of delay and making scheduling responsive to disturbances, while digital engineering shortens commissioning, supports reactive control and manages variation across the product lifecycle. The limitations are consistent: evidence is concentrated in simulations, benchmarks and single cases; model building remains costly, especially for smaller firms; and human roles and data availability shape what can be achieved. The gains are real at process and system level but have rarely been traced through to firm-level productivity.

6. Resource-Efficient Operations and an Integrated Productivity Framework

Energy has become a production variable rather than a fixed cost. A review of energy-aware production scheduling identified three shortcomings in current approaches: excessive reliance on deterministic assumptions, limited attention to dynamic operating conditions and under-use of regulatory mechanisms such as carbon trading. It called for scheduling systems that accommodate on-site renewable generation, battery storage, demand response and time-varying electricity prices (Georgiadis et al., 2025). Evidence on scale is emerging: in one optimisation study, energy-aware scheduling alone reduced energy cost by 23% and total cost by 7%, while combining it with on-site solar generation and battery storage saved 36% of energy cost and 15% of total cost (Karimi & Kwon, 2021).

Integrating energy into scheduling raises design questions about robustness and computation. An event-triggered hybrid scheduling paradigm was proposed to balance optimality, robustness to disturbances and computational cost in factories with renewable supply, and was demonstrated in a real manufacturing facility (Shao et al., 2024). In additive manufacturing, a systematic

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approach linked process-level control of power demand through parameter settings with scheduling that responded to time-varying electricity prices and demand charges, with numerical tests on industrial data demonstrating the improvement (Karimi et al., 2021). Learning-based methods can treat energy as an explicit objective: a deep reinforcement learning algorithm for automated guided vehicles jointly optimised material handling tardiness and energy consumption, including battery replacement, and proved both more efficient and environmentally cleaner than leading alternatives (L. Zhang et al., 2024).

Material efficiency offers a further productivity frontier. Making materials accounts for about 21% of global energy demand, and metals production for about 8% of total energy consumption. Reshaping end-of-life aluminium components through single point incremental forming proved more environmentally favourable than conventional or solid-state recycling because it involved fewer process steps and less material (Ingarao et al., 2021). In-line non-destructive inspection contributes in the same direction by catching defects before further value, material and energy are added (Lario et al., 2025). These studies show that productivity improvements can come from keeping material in use and avoiding the waste embedded in defects, not only from faster processing.

Resource objectives rarely come free, and the more careful studies make the trade-offs explicit. The comparative optimisation of energy-aware scheduling, solar generation and battery storage was designed to expose both the cost savings and the loss of time-related performance, measured through makespan, that different configurations produce (Karimi & Kwon, 2021). The vehicle scheduling study framed tardiness and energy as a bi-objective problem rather than collapsing them into a single cost (L. Zhang et al., 2024), and the event-triggered paradigm was motivated precisely by the tension among optimal performance, robustness and computational effort (Shao et al., 2024). For productivity management, the lesson is that energy and time dimensions must be reported side by side so that gains in one are not silently purchased with losses in the other.

Drawing these strands together, Figure 1 sets out a redefined productivity framework with six dimensions. Output productivity, measured as labour and total factor productivity, remains the anchor. Quality productivity captures good output as a share of total output and the material and energy embedded in defects. Time productivity covers cycle time, makespan, tardiness and responsiveness to disturbances. Energy productivity relates output to energy cost and carbon,

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taking account of when and from which sources energy is used. Material productivity tracks input per unit of good output and the share of material kept in use. Capability productivity reflects how quickly systems can be commissioned, reconfigured and improved, which digital engineering directly affects. Table 2 links each dimension to traditional and redefined measures and to the technologies and evidence that support improvement.

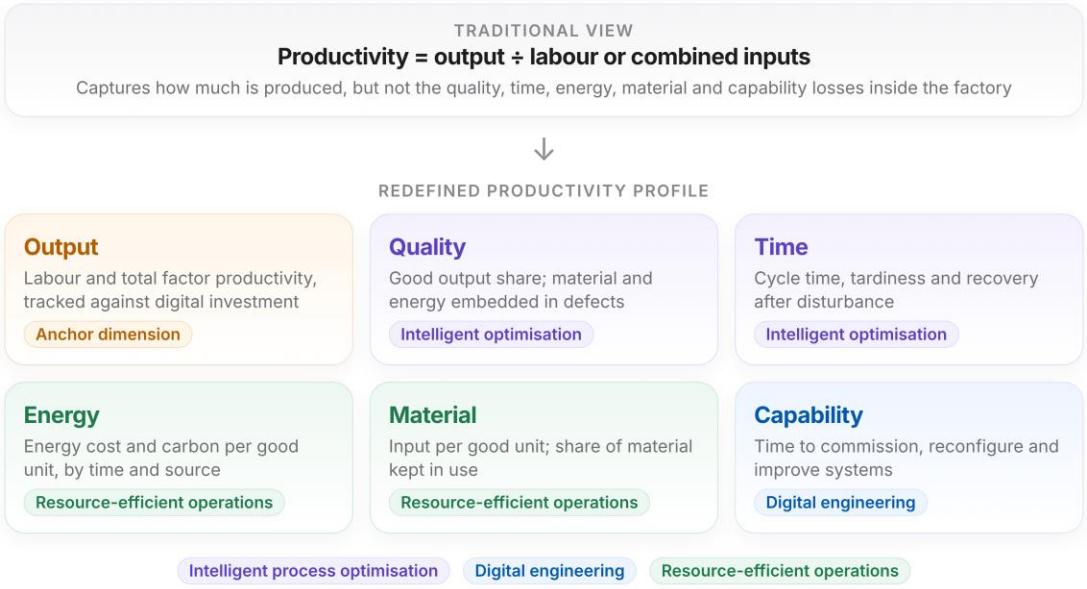


Figure 1. From traditional to redefined industrial productivity: six dimensions and their enabling approaches.

Figure 2 presents a layered capability architecture describing how the three approaches combine. A data foundation of sensors, inspection systems, event logs and energy metering feeds a modelling layer of digital twins, simulation and virtual commissioning built at appropriate fidelity. A decision layer applies defect prediction, process mining and learning-based or energy-aware scheduling to these models and data. Results are then assessed against the six productivity dimensions. A human layer runs through all levels: managers set the culture and priorities, engineers build and validate models, and operators supply knowledge and feedback (Wan & Leirmo, 2023). Performance management practices close the loop by ensuring that measurement leads to action (Naeem & Garengo, 2022).

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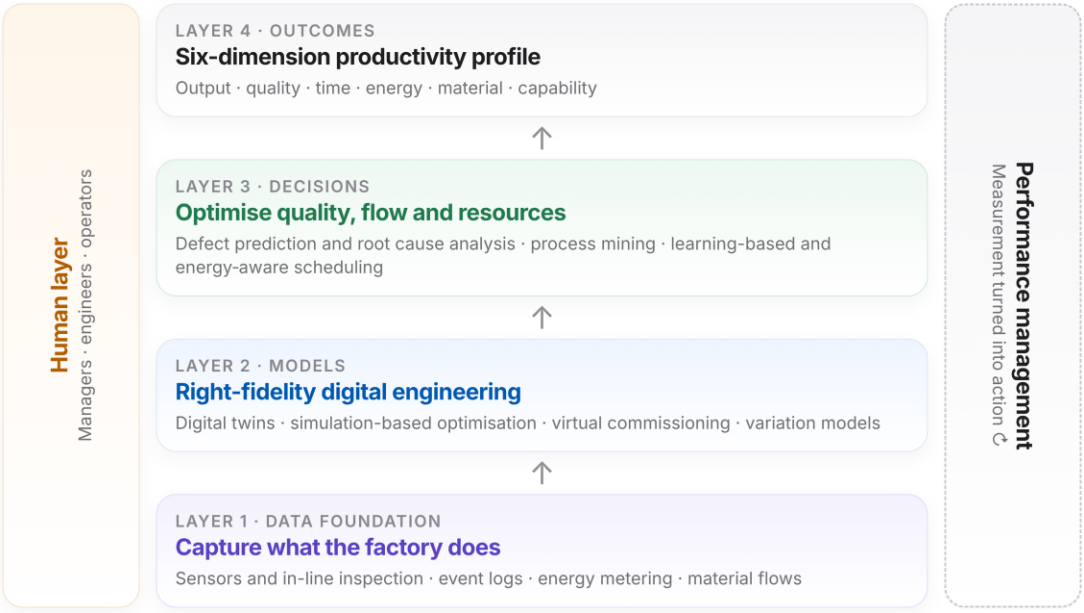


Figure 2. Layered capability architecture linking data, models, decisions and productivity outcomes.

The architecture implies a sequence for investment. Firms that lack reliable data and appropriate models are unlikely to benefit from advanced optimisation, which is consistent with econometric evidence that productivity gains appear only above thresholds of digital investment and infrastructure (Wu et al., 2025). Conversely, firms that have invested in data and models but have not developed management routines may accumulate information without improving outcomes.

Table 2. A redefined productivity framework: dimensions, measures and enablers

Dimension	Traditional measure	Redefined measure	Principal enablers	Supporting evidence
Output	Output per worker; total factor productivity	Value added per worker and per unit of capital, tracked against digital investment	Digital transformation; infrastructure; human capital	Wu et al. (2025); Wen and Zhan (2023)
Quality	Defect rate after inspection	Good output share; resources embedded in defects	In-line inspection; defect prediction; root cause analysis	Lario et al. (2025); Verna et al. (2023)
Time	Throughput per shift	Cycle time, tardiness and recovery after disturbance	Process mining; learning-based scheduling	Y. Lee et al. (2025); Yang and Xu (2022)

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Dimension	Traditional measure	Redefined measure	Principal enablers	Supporting evidence
Energy	Energy per unit	Energy cost and carbon per good unit, by time and source	Energy-aware scheduling; renewables and storage	Georgiadis et al. (2025); Karimi and Kwon (2021)
Material	Material yield	Input per good unit; share of material kept in use	Component reshaping; zero-waste inspection	Ingarao et al. (2021)
Capability	Rarely measured	Time to commission, reconfigure and improve	Virtual commissioning; right-fidelity digital twins	Striffler and Voigt (2023); L. Zhang et al. (2021)

In answer to RQ3, resource efficiency can be built into production decisions by treating energy price, energy source, carbon and material as objectives and constraints in scheduling and process planning, by preventing defects that waste embedded resources, and by redesigning processes to keep materials in use. The three approaches become mutually reinforcing when organised as layers of a single capability and evaluated against a multidimensional definition of productivity.

7. Discussion, Research Agenda and Limitations

Taken together, the evidence indicates that productivity in technology-intensive manufacturing is best understood as a profile rather than a single ratio. Traditional measures remain necessary, because they connect factory performance with firm and national outcomes, but they are insufficient to guide decisions about quality, scheduling, energy and materials. The evidence also explains why investment in digital technology does not automatically raise measured productivity: the effects pass through innovation, coordination and human capital, depend on thresholds, and are often realised in dimensions that conventional measures do not capture (Li et al., 2023; Wen & Zhan, 2023; Wu et al., 2025).

The synthesis also has a theoretical implication. Productivity research has largely treated technology as an input whose returns are captured in an aggregate residual, whereas engineering research treats it as a set of mechanisms acting on specific losses. The threshold and channel findings of the firm-level studies suggest that these views can be reconciled: aggregate effects emerge only when enough of the underlying mechanisms, in data, models and decisions, are in place and managed together. The layered architecture in Figure 2 can therefore be read as a proposition about complementarity, testable by asking whether firms that combine all layers show larger productivity effects than firms that invest in individual layers alone.

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A second implication concerns evidence. The most striking reported gains, such as large improvements in scheduling quality or energy cost, come from simulations, benchmark instances and single cases (Karimi & Kwon, 2021; Song et al., 2023; Yang & Xu, 2022). Firm-level studies, by contrast, estimate average effects of broad digital adoption without identifying which engineering practices produce them. Bridging this gap is the main task for future research and for managers building business cases.

For practitioners, four recommendations follow. Begin with data and measurement, ensuring that defects, cycle times, energy use and material flows are captured at the resolution needed for decisions. Build models at the fidelity required for the decision at hand rather than pursuing complete replication. Apply intelligent optimisation first where losses are greatest, typically defects and unstable schedules, and include energy and material objectives from the outset. Finally, develop performance management routines and human roles that turn data and models into action.

Firm size deserves particular attention. Virtual commissioning has so far been adopted mainly by large companies (Striffler & Voigt, 2023), the smaller manufacturers studied by Naeem and Garengo (2022) had developed measurement further than management, and human-centric zero-defect approaches face barriers of investment cost and resistance to changed work tasks (Wan & Leirmo, 2023). If the thresholds identified in firm-level studies apply with greater force to smaller firms, the redefined productivity agenda risks widening the gap between leaders and followers unless model-building effort, data infrastructure and skills become more accessible.

Research priorities follow from the gaps identified. Field studies should test learning-based and energy-aware scheduling in live production over extended periods and report robustness as well as average gains. Studies linking specific engineering practices, such as virtual commissioning or process mining, to firm-level productivity would connect the two evidence bases. The six-dimension framework needs operational definitions and validation, including methods for aggregating dimensions without obscuring trade-offs. Research on smaller firms should examine how model-building costs can be reduced and how thresholds of investment can be reached. Finally, the human-centric aspects of intelligent optimisation, including skills, trust and work design, deserve systematic study.

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The review has limitations. Its 30 articles cannot represent the full breadth of algorithmic and engineering research, and selection favoured studies with comparative or real-world validation. The econometric studies are drawn mainly from Chinese listed firms and European manufacturing, which limits generalisation. Many engineering results come from simulations or single cases. Abstracts formed the basis for some claims where full texts were unavailable, and one reviewer carried out the selection and coding. The framework and architecture are interpretive and require empirical testing.

8. Conclusion

Moving beyond traditional manufacturing requires moving beyond traditional definitions of productivity. The evidence reviewed here shows that intelligent process optimisation, digital engineering and resource-efficient operations each address losses that output-per-input measures overlook: defects, unstable schedules, slow commissioning, costly energy and wasted material. Their benefits are substantial at process and system level, and firm-level studies confirm positive productivity effects once investment and infrastructure thresholds are met.

A six-dimension productivity framework and a layered capability architecture offer a way to integrate these approaches and to measure what they achieve. For manufacturers, the message is to invest in data, models and management routines together, and to judge productivity by the good output delivered per unit of time, energy, material and capability as well as per worker. For researchers, the priority is to connect the engineering evidence with firm-level outcomes in real production settings.

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