

Digitalization and Industrial Energy Efficiency: Examining Whether Smart Manufacturing Accelerates Corporate Decarbonization

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Abstract

Manufacturers are adopting sensors, industrial internet of things platforms, manufacturing execution systems, digital twins, predictive maintenance, and artificial intelligence analytics, and these technologies are widely presented as a route to lower energy use and lower emissions. They can reduce energy per unit of output by making waste visible, tightening process control, and avoiding degraded equipment operation, and they can lower the carbon content of each unit of energy by enabling load shifting and renewable integration. The same technologies can also raise yield, capacity, and throughput, and a larger output can offset the savings. This study builds an evidence based framework for asking whether smart manufacturing accelerates corporate decarbonization. The evidence does not support a universal decarbonization effect: direct plant level evidence linking smart manufacturing to absolute corporate emissions is thin, the net energy effect of digital technology is described as conditional by several reviews, and the strongest empirical regularities concern the role of management capability and the economics of adoption. The paper therefore proposes a dual mechanism model in which smart manufacturing lowers emissions through product mix, energy efficiency, and carbon factor effects while also raising emissions through an output scale effect. It formalizes the net decarbonization effect as an exact four term accounting decomposition, derives a break even condition for output growth and a rebound rate, and develops research propositions, an empirical design, and a Smart Manufacturing Decarbonization Index (SMDI) for plant level research. The central implication is that smart manufacturing accelerates decarbonization only when its efficiency, mix, and carbon factor gains outweigh the additional emissions created by higher output.

1. Introduction

Manufacturing is a large and difficult part of the corporate decarbonization problem because industrial emissions come from process heat, motors and drives, compressed air, steam, refrigeration, and the electricity that powers them, and these loads are embedded in production systems that firms cannot easily stop or redesign. Firms therefore look for options that cut energy use without cutting output. Digitalization is among the most prominent of these options. Sensors and industrial internet of things platforms provide continuous data on machine and process behavior, manufacturing execution systems and digital twins support scheduling and simulation, predictive maintenance keeps equipment operating near design efficiency, and artificial intelligence analytics promise automatic optimization of setpoints and loads. The IEA (27) describes digitalization as a significant force that can change energy demand across sectors, and that discussion has been carried into the industrial setting through the Industry 4.0 agenda (19; 3).

Whether these technologies accelerate corporate decarbonization is nonetheless uncertain. The optimistic account is that visibility and control reduce the energy needed per unit of output and that integration with the energy system lowers the carbon content of what remains. The cautious account is that digitalization has its own energy footprint (32), that the net energy effect of information and communication technology depends on rebound and growth effects (26; 29), and that technologies which raise productivity can raise output (23; 14). The rebound literature has long warned that efficiency gains can be partly or wholly offset when cheaper or faster production induces more production (28; 12; 24; 35). Environmental performance at the firm level is further shaped by management capability: plants that manage energy systematically tend to be more energy efficient (11; 31), and the economics of adopting efficiency projects are often less favorable than engineering estimates suggest (1; 18). These strands are rarely combined into a single account of corporate decarbonization.

This paper therefore asks: *Does digitalization, in the form of smart manufacturing, accelerate corporate decarbonization?* The question is framed at the plant and firm level and is broken into four research questions.

- RQ1** Does smart manufacturing lower the energy and carbon intensity of output through product mix, energy efficiency, and carbon factor channels?
- RQ2** Does it raise total output and therefore energy demand (scale and rebound)?
- RQ3** Under what conditions do the decarbonization effects outweigh the scale effect?
- RQ4** How can the two sets of effects and the organizational processes behind them be measured at the plant level?

The paper makes five contributions. First, it integrates smart manufacturing and corporate decarbonization into one framework that treats digital technology as decision infrastructure rather than as an inherently green technology. Second, it separates the decarbonization effect from the output scale effect through an exact four term accounting decomposition, and it derives a break even condition and a rebound rate. Third, it organizes the mechanisms through which digital technologies affect plant energy use into five measurable channels. Fourth, it proposes measurable indicators and a composite index for plant level research. Fifth, it states testable propositions for future work with panel data, plant meter data, and firm level emissions disclosures.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 develops the theoretical framework. Section 4 describes the methodology and measurement. Section 5 synthesizes the evidence and illustrates the framework. Section 6 discusses implications, Section 7 sets out limitations and a research agenda, and Section 8 concludes. Figure 1 summarizes the proposed framework.

2. Literature Review

2.1 Smart Manufacturing, Industry 4.0, and Sustainability

Smart manufacturing is used here to mean the integration of sensing, connectivity, data analytics, and automated control in production, so that machines, processes, and energy systems can be monitored and adjusted in near real time. It is closely related to the Industry 4.0 concept

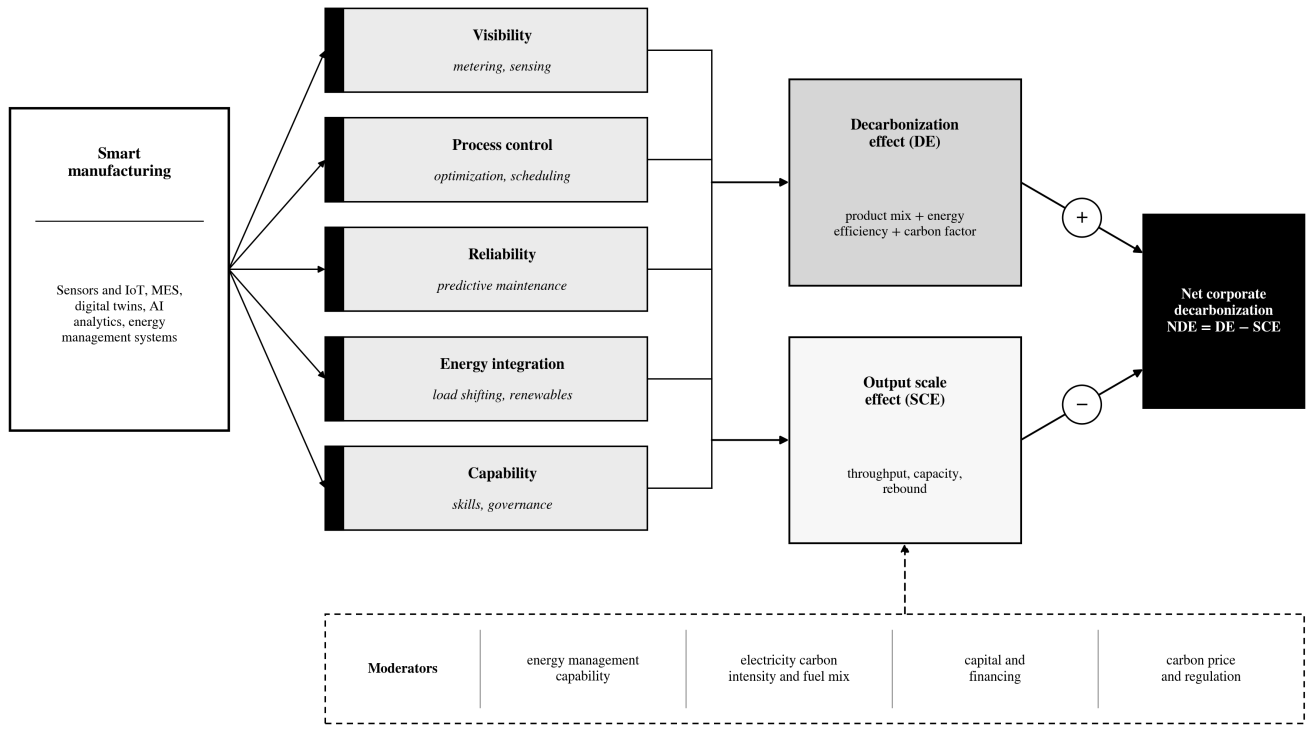


Figure 1. Smart manufacturing with corporate decarbonization through five plant level mechanisms.

and covers industrial internet of things platforms, manufacturing execution systems, digital twins, predictive maintenance, advanced process control, and energy management systems.

A sizeable literature assesses the sustainability implications of these technologies, and most of it is conceptual, scenario based, or based on expert assessment. Ghobakhloo (19) identifies sustainability functions that Industry 4.0 technologies can perform and discusses the conditions for realizing them. Bai et al. (3) assess a set of Industry 4.0 technologies against sustainability criteria, and Bonilla et al. (10) examine impacts and challenges in a scenario based analysis. Stock and Seliger (36) discuss opportunities for sustainable manufacturing, and Shrouf et al. (34) describe how internet of things based smart factories could support energy management in production. These studies establish that a plausible set of pathways exists. They do not, however, establish that realized plant level emissions fall after adoption, because they mostly describe potential rather than measured outcomes.

2.2 Digitalization and Energy Use

Reviews of the digitalization and energy literature find that the net effect is not determined in advance. Horner et al. (26) review the indirect energy effects of information and communication technology and report a wide range of estimates with substantial uncertainty about the direction of the net effect. Lange et al. (29) organize the channels into efficiency effects, rebound effects, economic growth effects, and structural change effects, and argue that whether digitalization reduces energy demand depends on how these compete. Digital infrastructure also consumes energy: Masanet et al. (32) show that data center energy use rose only modestly over a period in which computing output grew several-fold, which illustrates both a large efficiency gain and a reminder that the infrastructure itself has a footprint. For a manufacturer the implication is that the energy used by the digital system should be counted against the savings it enables.

2.3 Industrial Energy Efficiency and Management Capability

Energy efficiency investments in industry are shaped by information, capital, and organizational factors. Gillingham et al. (20) and Gerarden et al. (18) review the economics of energy efficiency and the reasons why apparently attractive projects are not always adopted. Anderson and Newell (1) study plants that received energy audits and find that adoption of recommended projects depends on economic characteristics such as costs and payback, and that recommendations are not adopted automatically. Management capability appears repeatedly as a

condition of performance. Boyd and Curtis (11) report that firm management practices are linked to energy efficiency in United States manufacturing, and Martin et al. (31) study how management practices and organizational structure relate to energy efficiency in United Kingdom manufacturing. More generally, Bloom and Van Reenen (9) show that management practices vary widely across firms and countries and are related to performance. Smart manufacturing generates information, but this literature suggests that information only becomes savings when an organization has the capability to act on it.

2.4 Productivity, Complementarities, and Output Effects

Digital and automation technologies are productivity technologies. Graetz and Michaels (23) use industry level data for several countries and report that increased use of industrial robots is associated with higher labor productivity and output. Brynjolfsson and Hitt (13) argue that returns to information technology depend on complementary organizational change, and Brynjolfsson et al. (14) describe a productivity J-curve in which the returns to general purpose technologies appear with a lag because intangible complements must first be built. For decarbonization these results matter in two ways. If smart manufacturing raises output, it creates the scale effect that works against energy savings. If returns arrive with a lag, the energy and emissions effects may also appear with a lag, and a short window can misstate them.

2.5 Artificial Intelligence, Automation, and Carbon Outcomes

Direct empirical evidence that links digital and automation technologies with carbon outcomes in industry is limited and mostly aggregate. Liu et al. (30) study the industrial sector in China and report that artificial intelligence is associated with lower carbon intensity. Such a finding supports the intensity channel, but it concerns carbon intensity rather than absolute emissions, and sector level data cannot show whether output growth offset the intensity gains inside individual firms. This is the main empirical gap that the present framework addresses.

2.6 Rebound, Scale, Composition, and Technique

The distinction between scale, composition, and technique has a long history in environmental economics. Grossman and Krueger (25) separated the environmental effects of economic activity into a scale effect from larger output, a composition effect from changes in the mix of activities, and a technique effect from changes in production methods, and Copeland and Taylor (16) review the approach. The related IPAT identity (17) expresses impact as the product of population, affluence,

and technology. Index decomposition methods allow such changes to be attributed exactly, and Ang (2) compares methods and discusses the properties of log mean Divisia decomposition. The rebound literature shows that efficiency improvements can be offset by higher use (28; 12; 24), and Sorrell and Dimitropoulos (35) distinguish direct, indirect, and economy wide mechanisms, while Gillingham et al. (21) review evidence on the size of rebound effects and its implications for policy. Smart manufacturing raises the same issue at the plant level: an efficiency or mix gain can be offset if digital capability also increases output. Section 3 adapts the scale, composition, and technique logic to the plant decision pathway and adds a fourth term for the carbon content of energy.

2.7 Corporate Carbon Accounting and Energy-System Integration

Corporate decarbonization is measured through greenhouse gas inventories. The WRI and WBCSD (38) corporate standard distinguishes emissions from owned sources (Scope 1) from emissions from purchased electricity, steam, heat, and cooling (Scope 2), and the Sotos (39) guidance requires dual reporting of Scope 2 emissions on a location based and a market based method. The choice matters for the present question. A plant that cuts its electricity use lowers location based Scope 2 emissions in proportion to the local grid factor, whereas a plant that shifts load or procures lower carbon electricity changes the carbon factor rather than the energy quantity. The framework therefore treats the carbon factor as a separate term and requires that the accounting method be stated.

2.8 Research Gap

Five gaps are identified. First, much of the smart manufacturing literature assesses potential or adoption rather than realized emissions. Second, empirical work on digitalization and energy often examines economy wide or sector level energy use rather than plant level outcomes. Third, efficiency studies in industry focus on intensity and do not always report absolute emissions together with output. Fourth, the intensity, mix, carbon factor, and output scale effects are rarely examined together in a single accounting framework. Fifth, a unified measurement framework connecting digital capability, management capability, energy intensity, output, and corporate emissions is still missing. This study addresses these gaps through a dual effect framework. Table 1 summarizes the evidence base.

3. Theoretical Framework

3.1 Smart Manufacturing as Energy Decision Infrastructure

The paper treats smart manufacturing as an energy decision infrastructure rather than an inherently green technology. A sensor network can reveal an idling compressor, but the saving occurs only if someone acts on the signal. A digital twin can identify a lower energy production schedule, but it can equally be used to raise throughput. Predictive maintenance can keep a furnace at design efficiency, but it also raises uptime and therefore capacity. The environmental result is therefore a joint outcome of the technology, the organization using it, and the energy system supplying it.

The framework includes five plant level mechanisms: visibility, process control, reliability, energy-system integration, and capability (Table 2). Visibility is the metering and sensing of energy and process data. Process control is the optimization of setpoints, scheduling, and yield. Reliability is the use of condition monitoring and predictive maintenance to keep assets in efficient operation. Energy-system integration is the coordination of plant loads with on-site generation, storage, electrified heat, and grid conditions. Capability is the skill and governance needed to turn data into action, including energy management systems and standards.

3.2 Accounting Framework: Scale, Mix, Efficiency, and Carbon Factor

Let a plant or firm's emissions in a period be

$$C = Q \sum_{k=1}^n s_k e_k f_k = Q \bar{I}, \quad \bar{I} = \sum_{k=1}^n s_k e_k f_k, \quad (1)$$

where Q is total output, s_k is the output share of product line or process k with $\sum_k s_k = 1$, e_k is the energy intensity of k (energy per unit of output), f_k is the emission factor of the energy used by k (emissions per unit of energy), and $\bar{I}$ is the average carbon intensity of output. Superscripts B and A denote the situation before and after exposure to smart manufacturing.

The output scale effect is the change in emissions caused by a change in total output at baseline shares, energy intensities, and emission factors:

$$\text{SCE} = (Q^A - Q^B) \sum_k s_k^B e_k^B f_k^B. \quad (2)$$

The decarbonization effect has three parts, each defined as an emission reduction so that a positive value is favorable:

$$\text{MIX} = -Q^A \sum_k (s_k^A - s_k^B) e_k^B f_k^B, \quad (3)$$

$$\text{EFF} = -Q^A \sum_k s_k^A (e_k^A - e_k^B) f_k^B, \quad (4)$$

$$\text{CFE} = -Q^A \sum_k s_k^A e_k^A (f_k^A - f_k^B), \quad (5)$$

$$\text{DE} = \text{MIX} + \text{EFF} + \text{CFE}. \quad (6)$$

The mix effect captures shifts in output toward less carbon intensive product lines. The efficiency effect captures reductions in energy per unit within a line, such as those from tighter process control and avoided waste. The carbon factor effect captures reductions in emissions per unit of energy, such as those from load shifting, on-site renewable generation, or electrified heat. The net decarbonization effect is

$$\text{NDE} = \text{DE} - \text{SCE} = C^B - C^A. \quad (7)$$

The last equality is an exact identity: adding the four terms telescopes to $Q^A \sum_k s_k^A e_k^A f_k^A - Q^B \sum_k s_k^B e_k^B f_k^B$. The decomposition is sequential, with scale first, then mix, then efficiency, then carbon factor, so the split between terms depends on that ordering, although their sum does not. Log mean Divisia methods (2) give an order independent alternative and are recommended for empirical work. This is an accounting identity rather than an empirical estimate. A positive NDE means that emissions fall, and a negative value means that additional output outweighs the decarbonization gains. Figure 2 shows how the terms can behave as digitalization intensity rises. Curves use assumed parameters, $\rho(d) = 0.14(1 - e^{-4d})$ and $g(d) = 0.20d^{1.4}$, with $\text{DE} = (1 + g)\rho$ and $\text{SCE} = g$ as shares of baseline emissions. They are not estimates.

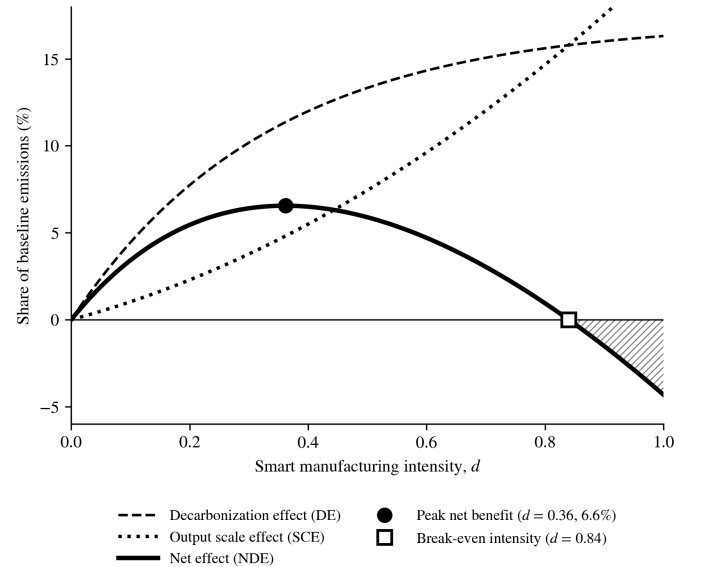


Figure 2. Trade off between the decarbonization effect (DE), the output scale effect (SCE), and the net effect (NDE).

3.3 Break Even Condition and Rebound

Because $C = Q\bar{I}$, emissions do not rise if and only if output growth is no larger than the proportional fall in average carbon intensity. Writing $g = Q^A/Q^B - 1$ for output growth and $\rho = 1 - \bar{I}^A/\bar{I}^B$ for the proportional reduction in average intensity, the net effect is non-negative

Table 1. Evidence Relevant to Smart Manufacturing and Corporate Decarbonization

Study	Context	Main evidence as reported	Interpretation
Boyd and Curtis (11)	United States manufacturing plants	Management practices linked with energy efficiency	Capability condition
Martin et al. (31)	United Kingdom manufacturing firms	Management practices and organizational structure related to energy efficiency	Capability condition
Anderson and Newell (1)	United States industrial plants after energy audits	Adoption of recommended projects depends on economic characteristics	Adoption economics
Liu et al. (30)	China industrial sector	Artificial intelligence associated with lower carbon intensity	Intensity channel (aggregate)
Graetz and Michaels (23)	Industries in several countries	Robot use associated with higher productivity and output	Scale pathway
Brynjolfsson et al. (14)	United States, aggregate	Returns to general purpose technology arrive with a lag because intangible complements must be built	Lag and complementarity
Masanet et al. (32)	Global data centers	Energy use grew modestly while computing output grew several-fold	Digital infrastructure footprint
Lange et al. (29)	Review	Efficiency, rebound, growth, and structural effects compete; net effect conditional	Mixed
Horner et al. (26)	Review	Indirect energy effects of ICT span a wide range with large uncertainty	Mixed
Gillingham et al. (21)	Review	Rebound effects are an empirical question with policy implications	Rebound
Gerarden et al. (18)	Review	Energy efficiency gap and its possible explanations	Adoption conditions
Ghobakhloo (19); Bai et al. (3)	Conceptual and assessment studies	Industry 4.0 technologies can perform sustainability functions under conditions	Potential, not realized outcomes
Bonilla et al. (10); Stock and Seliger (36); Shrouf et al. (34)	Scenario and conceptual studies	Opportunities and challenges for sustainable and energy efficient manufacturing	Potential, not realized outcomes

Table 2. Five Plant Level Mechanisms and Their Environmental Pathways

Mechanism	Definition	Decarbonization pathway	Scale pathway	Example indicator
Visibility (EV)	Metering and sensing of energy and process data	Identifies waste, idle loads, and drift; enables benchmarking	Exposes bottlenecks and capacity slack that can be used to expand output	Share of energy sub-metered; data latency
Process control (PC)	Optimization of setpoints, scheduling, and yield	Lowers energy per unit through tighter control and less scrap	Raises throughput and shortens lead times	Share of load under closed-loop control; first pass yield
Reliability (PM)	Condition monitoring and predictive maintenance	Avoids operation in degraded, inefficient states	Raises uptime and effective capacity	Unplanned downtime; share of assets monitored
Energy-system integration (EI)	Load shifting, on-site renewables, electrified heat, demand response	Lowers the carbon factor of each unit of energy	Eases energy constraints on expansion	Flexible share of load; hourly carbon factor
Capability (MC)	Skills, governance, and energy management systems	Converts data into implemented savings	Competes with growth projects for capital and attention	Energy manager staffing; audit project adoption rate

when

$$1 + g \leq \frac{\bar{I}^B}{\bar{A}} \iff g \leq g^* = \frac{\rho}{1 - \rho}. \quad (8)$$

The break even growth rate g^* is the largest increase in output that a given mix, efficiency, and carbon factor improvement can absorb. If smart manufacturing lowers average intensity by 8%, for example, output can grow by about 8.7% before emissions start to rise. Figure 2 shows how the pattern can arise when decarbonization gains have diminishing returns while scale effects keep accumulating: net benefits first rise, peak, and then fall below zero.

The same algebra gives a rebound rate for energy. Suppose smart manufacturing lowers energy intensity by a proportion ε at constant output, so that the engineering saving is εE^B , and output then grows by g . Realized energy use is $(1 + g)(1 - \varepsilon)E^B$, so realized savings are $E^B[\varepsilon - g(1 - \varepsilon)]$ and the rebound rate is

$$R = 1 - \frac{\text{realized saving}}{\text{engineering saving}} = \frac{g(1 - \varepsilon)}{\varepsilon}. \quad (9)$$

With $\varepsilon = 8\%$ and $g = 4\%$ the rebound rate is $R = 46\%$, and with $g = 10\%$ it is $R = 115\%$, which is a backfire in the sense that energy use rises. Backfire ($R > 1$) occurs exactly when $g > \varepsilon/(1 - \varepsilon)$, which is the break even condition in Equation (8) with $\rho = \varepsilon$. Because carbon factors can change independently of energy quantities, the rebound rate for emissions differs from the rebound rate for energy.

3.4 Organizational Mechanism

The pathway from technology to emissions runs through the organization. It runs from the deployed system through a signal, a decision, an implementation, and a net outcome (Figure 3). If p_1 is the probability that a relevant signal is generated and seen, p_2 that it leads to a decision, p_3 that the decision is implemented, and p_4 that the implemented change produces a net emissions benefit after rebound, the share of deployments completing the chain is

$$\Pi = \prod_{j=1}^4 p_j. \quad (10)$$

Because the probabilities multiply, modest failure at every stage compounds into a small overall effect. The pathway is expected to be

stronger where plants have energy management capability, ownership of energy performance, and funding for the changes that data identify.

3.5 Moderators and Boundary Conditions

The framework expects management capability and energy-system integration to moderate the pathway, and it treats the carbon intensity of electricity, the fuel mix, capital availability, product market conditions, and regulation as boundary conditions. The same system can have different consequences where the electricity grid is carbon intensive, where on-site generation is available, where the plant is capacity constrained, or where a carbon price makes savings more valuable.

4. Methodology

4.1 Research Design

The study is a structured secondary evidence synthesis. Peer reviewed journal articles, established academic reviews, and authoritative institutional materials are prioritized. The unit of analysis is the plant or firm decision pathway. The study does not claim a new plant dataset or a new causal estimate; it develops a framework for future empirical testing.

Four evidence groups are used: studies of digitalization and energy use; studies of industrial energy efficiency, adoption, and management; studies of productivity and output effects of digital and automation technologies; and sustainability assessments of Industry 4.0 and smart manufacturing. Each study was coded by level of analysis (plant or firm, industry or economy, review or conceptual) and by the direction of its reported findings on energy or carbon intensity, output, rebound, adoption conditions, and potential (Section 5.1).

Table 3. Evidence Selection Framework

Criterion	Included	Excluded
Date	Published before 2023	Published in 2023 or later
Quality	Peer reviewed research and authoritative evidence	Unsupported commentary
Topic	Digitalization, industrial energy, productivity, rebound	Unrelated digital technologies
Outcome	Energy use, intensity, output, emissions, adoption	Outcomes without energy relevance
Unit	Plant, firm, industry, economy	Purely technical control studies

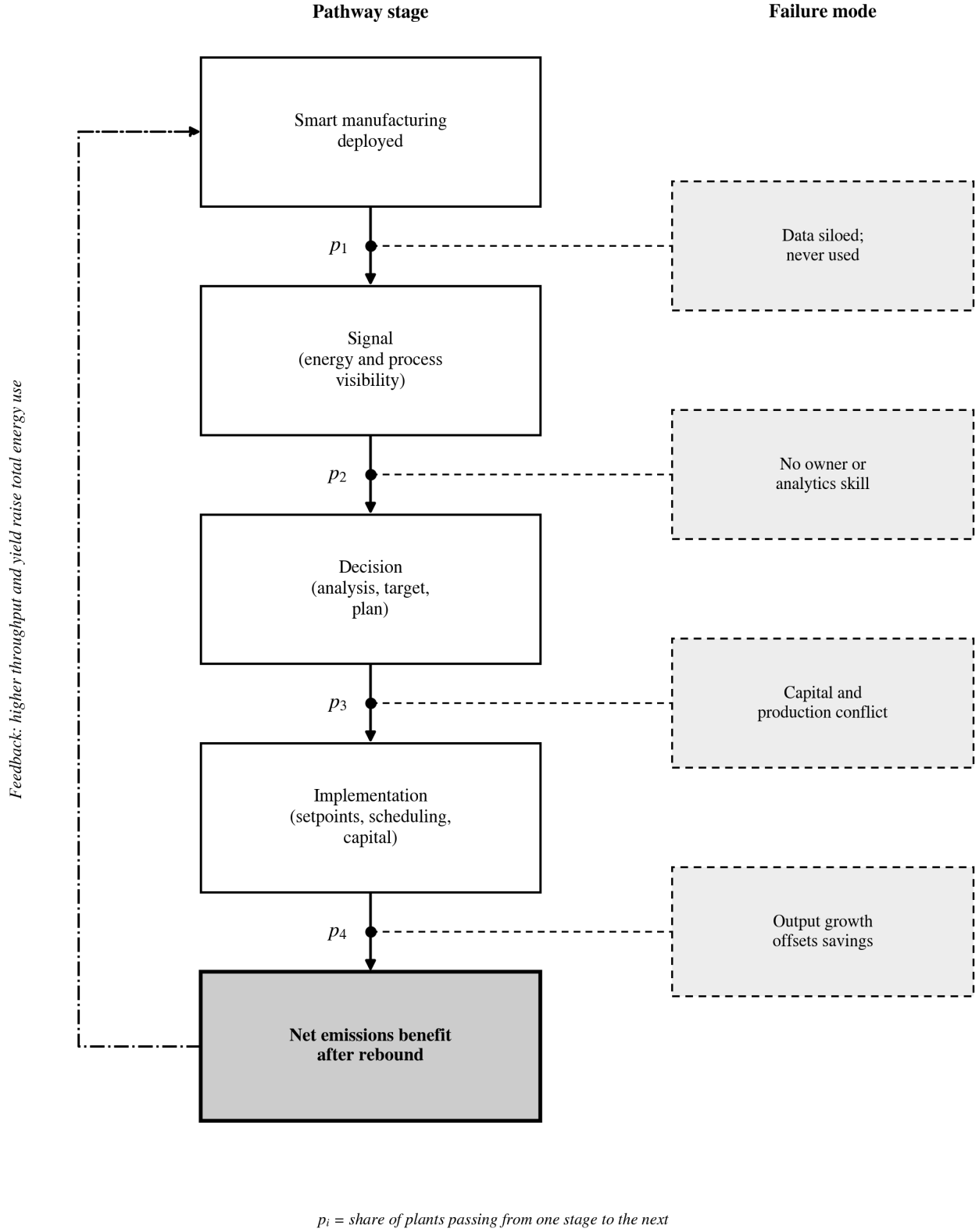


Figure 3. Organizational pathway from deployed smart manufacturing systems to emissions outcomes, with typical failure points and the feedback that can raise total energy use.

4.2 Measurement Variables

The primary independent construct is smart manufacturing intensity (SMI). It can be measured with the share of energy sub-metered, the share of load under closed-loop control, the share of assets under condition monitoring, the adoption of manufacturing execution or digital twin systems, or composite indices. The main dependent constructs are energy intensity, the carbon factor, output, and absolute emissions, which together determine the net effect. Environmental outcomes should include both intensity and absolute measures. Table 4 lists the constructs.

4.3 Smart Manufacturing Decarbonization Index

The study proposes a Smart Manufacturing Decarbonization Index (SMDI) built from five components that correspond to the mechanisms in Table 2: energy visibility (*EV*), process control (*PC*), predictive maintenance (*PM*), energy-system integration (*EI*), and management capability (*MC*). Each raw indicator z_{jh} for plant h is first rescaled to $[0, 100]$,

$$\tilde{z}_{jh} = 100 \frac{z_{jh} - z_j^{\min}}{z_j^{\max} - z_j^{\min}}, \quad (11)$$

Table 4. Constructs, Indicators, and Candidate Data for Plant Level Research

Construct	Symbol	Example indicators	Unit	Candidate data source
Smart manufacturing intensity	SMI	Share of energy sub-metered; closed-loop controlled load; monitored assets; system adoption dates	Share or index	Plant survey; vendor installation records
Energy intensity	EI	Energy per unit of output by line; specific energy consumption	GJ per unit	Meter data; utility bills; production records
Carbon factor	CF	Emissions per unit of energy by fuel and electricity source; location and market based Scope 2	tCO ₂ e per GJ	Fuel invoices; grid emission factors; supplier data
Output and mix	Q, s	Output volume; product line shares; capacity utilization	Units; shares	ERP and production records
Emissions	CE	Scope 1 and Scope 2 emissions; electricity use; fuel use	tCO ₂ e; kWh	Inventories; utility bills; emission factors
Management capability	EMC	Energy management system; audit adoption rate; energy manager staffing; management practice score	Score (0–100)	Plant survey; certification records
Controls	X	Plant size, age, sector, ownership, energy prices, capacity utilization	Various	Survey; administrative data

and the index is the weighted sum

$$\text{SMDI}_h = w_1 EV_h + w_2 PC_h + w_3 PM_h + w_4 EI_h + w_5 MC_h, \quad \sum_{j=1}^5 w_j = 1. \quad (12)$$

Equal weights may be used in exploratory work, while factor analysis or expert weights may be used in more advanced studies. Weights matter because they can change rankings. Figure 4 shows three hypothetical plants: under equal weights, plant C (integration-led) scores 59.0 and plant B (control-led) scores 57.0, but under weights that emphasize process control, as might be appropriate in a plant whose emissions come mainly from process heat, B scores 65.8 and C scores 53.0, so the ranking reverses. Weight sensitivity should therefore be reported. The SMDI describes capability and deployment; it does not replace the absolute outcome measure NDE, which is estimated separately.

Table 5. SMDI Components and Example Scoring

Component	Example indicators	Scoring
EV: energy visibility	Share of energy sub-metered; data latency; dashboard use	Min–max
PC: process control	Share of load under closed-loop control; advanced process control coverage	Min–max
PM: predictive maintenance	Share of critical assets under condition monitoring; unplanned downtime	Min–max
EI: energy-system integration	Flexible load share; on-site renewable share; electrified heat share	Min–max
MC: management capability	Energy management system in place; audit adoption; staffing	Score (0–100)

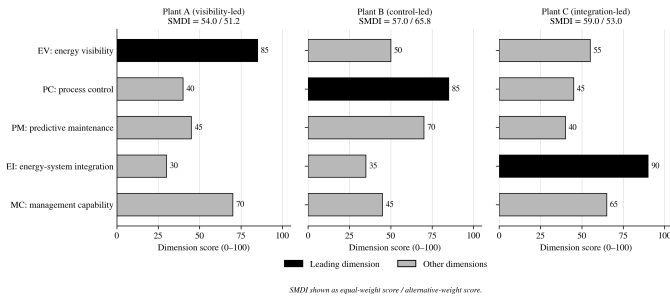


Figure 4. Component profiles of three hypothetical plants.

4.4 Empirical Models for Future Testing

Because Equation (1) implies $\ln C = \ln Q + \ln EI + \ln CF$ when output, energy intensity, and the carbon factor are measured consistently, the net effect can be recovered from three parallel plant panel regressions. For each outcome $y \in \{\ln EI, \ln CF, \ln Q\}$,

$$y_{it} = \alpha_0^y + \alpha_1^y \text{SMI}_{it} + \alpha_2^y \text{EMC}_{it} + \alpha_3^y X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \quad (13)$$

where μ_i represents plant effects and λ_t represents time effects. The total proportional effect of smart manufacturing on emissions is then the sum of the three coefficients,

$$c = \alpha_1^{EI} + \alpha_1^{CF} + \alpha_1^Q, \quad (14)$$

where α_1^{EI} is expected to be negative (efficiency and mix), α_1^{CF} is expected to be zero or negative (carbon factor), and α_1^Q is expected to be positive (scale). The sign of c depends on which side is larger, which mirrors NDE in Equation (7), and $c \leq 0$ exactly when $\alpha_1^Q \leq$

$-(\alpha_1^{EI} + \alpha_1^{CF})$. This structure separates the intensity and scale pathways while respecting the accounting identity. Plant fixed effects remove time invariant differences, but adoption of smart manufacturing is not random. Credible identification therefore calls for event study designs around system installation dates that use estimators robust to staggered adoption (15; 37), since two way fixed effects estimates can be biased under heterogeneous timing (22), together with instruments based on plausibly exogenous variation in vendor roll out or connectivity infrastructure, and placebo tests on outcomes that should not respond. Because returns to digital technology can arrive with a lag (14), dynamic specifications with several post adoption periods are required. Legend values give the SMDI under equal weights and under process control weighted weights ($w = 0.15, 0.40, 0.20, 0.10, 0.15$). The profiles are illustrative and show how weights can reverse rankings.

4.5 Moderation Tests

Management capability is expected to strengthen the relationship between smart manufacturing and energy intensity reduction,

$$\begin{aligned} \ln EI_{it} = & \beta_0 + \beta_1 \text{SMI}_{it} + \beta_2 \text{EMC}_{it} \\ & + \beta_3 (\text{SMI}_{it} \times \text{EMC}_{it}) \\ & + \beta_4 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \end{aligned} \quad (15)$$

and a negative β_3 would indicate a larger intensity reduction among plants with greater management capability. The carbon intensity of the energy supply is expected to condition the absolute emissions benefit. The same specification with emissions in levels as the outcome and the baseline grid or fuel carbon factor in place of EMC tests proposition P5, where a negative interaction coefficient indicates a larger absolute emissions reduction where the energy supply is more carbon intensive. Figure 5 presents the recommended measurement architecture.

4.6 Data for a Bangladesh Application

A study in Bangladesh could combine a plant survey module, utility and fuel records, and production data for energy intensive manufacturing such as textiles and garments, where energy is used in boilers, dyeing and finishing, compressed air, and captive generation. Candidate sources include the establishment surveys of the Bangladesh Bureau of Statistics, energy audit records held by public energy agencies, plant electricity and gas billing records, and a purpose built survey that measures smart manufacturing deployment and management capability. Emission factors for the national electricity mix and for gas and captive generation should be applied consistently to convert energy into f_k , and both location based and market based Scope 2 values should be reported where applicable. Access, sampling, confidentiality, and consent conditions must be confirmed before fieldwork.

4.7 Validation Plan

The index and the decomposition should be validated before they are used for inference. For the SMDI, content validity can be reviewed by experts, dimensionality tested with confirmatory factor analysis, measurement invariance checked across sectors and plant sizes, and reliability examined through repeated measurement. For the decomposition, results should be reported under alternative orderings and with a log mean Divisia decomposition, under alternative emission factors and Scope 2 methods, and with and without the energy used by the digital system itself.

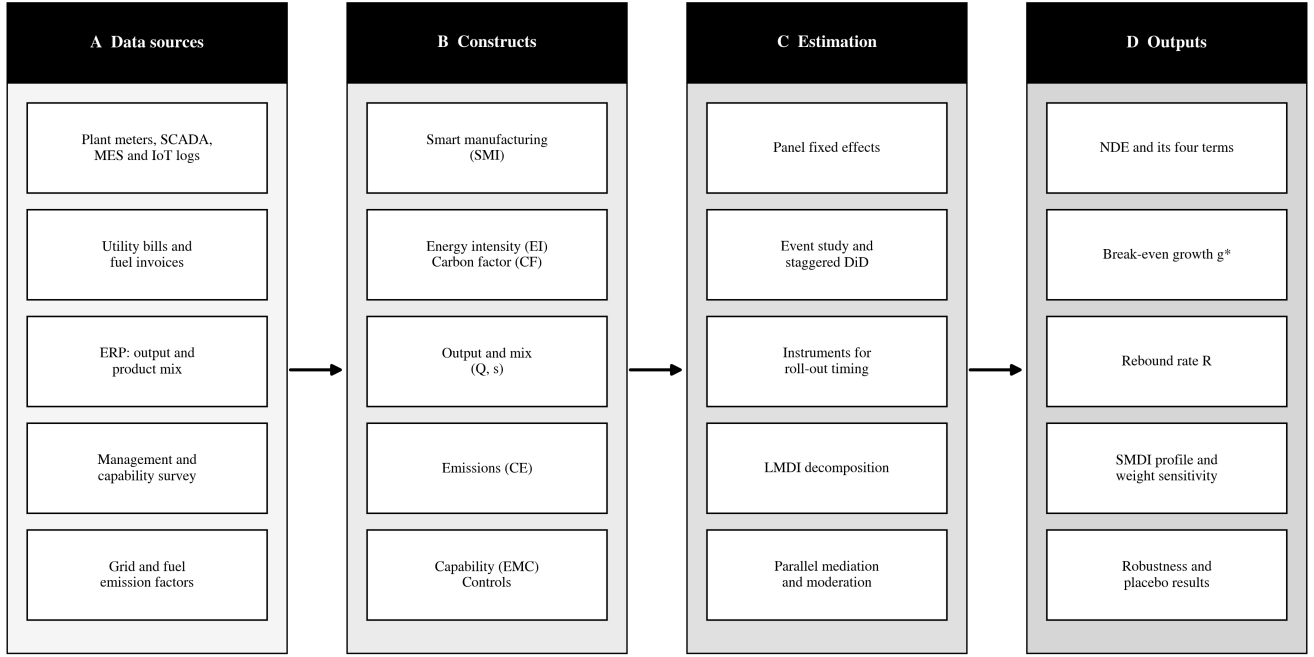


Figure 5. Recommended empirical measurement architecture for plant level smart manufacturing research.

5. Analysis and Results

5.1 Evidence Synthesis

The literature provides no single direction of effect. Figure 6 classifies the reported findings of the reviewed studies by level of analysis and by type of finding, and four patterns emerge.

First, the most consistent plant level regularity concerns capability and economics rather than technology: management practices are associated with better energy performance, and adoption of efficiency projects depends on economic conditions (11; 31; 1; 18). Second, evidence that digital and automation technologies raise productivity and output is consistent where it is measured, and the benefits can arrive with a lag (23; 14), which establishes the conditions for a scale effect. Third, reviews of digitalization and energy conclude that the net effect depends on the balance of efficiency, rebound, and growth channels (26; 29; 21), and the single sector level study of carbon outcomes reports lower carbon intensity (30). Fourth, the Industry 4.0 sustainability studies largely describe potential (19; 3; 10; 36; 34). Direct evidence that connects smart manufacturing to absolute corporate emissions at the plant level is therefore thin. The contrast between favorable intensity evidence and the absence of absolute emissions evidence may reflect what is measured as much as real differences in effects, and it supports measuring intensity and absolute outcomes together.

5.2 Scale, Mix, Efficiency, and Carbon Factor: A Numerical Illustration

The decomposition in Section 3.2 can be illustrated with a hypothetical plant. The numbers below are assumed for exposition and are not estimates from data. The plant produces 1,000 units per period across five product lines. Baseline output shares are 25%, 30%, 20%, 10%, and 15% for castings and forgings, machined components, assembled units, electronics modules, and coated and finished goods. Energy intensities are 2.00, 1.00, 0.50, 0.60, and 1.20 GJ per unit, and emission factors are 0.062 tCO₂e per GJ for the gas intensive first line, 0.120 for the three electricity based lines, and 0.080 for the coating line, so baseline emissions are $C^B = 100.60$ tCO₂e. After smart manufacturing is deployed, output rises by $g = 4\%$, output shifts away from castings and coating toward assembly and electronics, energy intensities fall by 2 to 6% through tighter control and avoided waste, and emission factors fall by 1 to 3% through load shifting and on-site generation. Table 6 reports the decomposition and Figure 7 shows it as a waterfall.

In this example the scale effect raises emissions by 4.02 tCO₂e, while mix lowers them by 1.46, efficiency by 4.86, and carbon factor by 2.40, so SCE = 4.02, DE = 8.72, and NDE = +4.69: emissions

fall from 100.60 to 95.91 tCO₂e. Energy per unit of output falls by 7.7%, but total energy falls by only 4.0% because of output growth. The same plant would have a negative NDE if it made no green shift at all, because scale alone would raise emissions by 4.02. Table 7 and Figure 8 show how the outcome depends on the strength of the shift and on output growth. The break even growth rate rises from 3.1% under a weak shift to 19.4% under a strong shift, so the same rate of output growth can be environmentally beneficial in one setting and harmful in another. Under the moderate shift, 4% growth is absorbed but 10% growth is not (NDE = -0.84).

Figure 9 generalizes the scenarios by showing the net change in emissions across combinations of intensity reduction ρ and output growth g . The frontier $g = \rho / (1 - \rho)$ separates combinations in which emissions fall from those in which they rise, and it makes clear that a modest intensity gain leaves little room for growth. Squares mark the break even growth rate g^* where NDE equals zero. Scenarios are those in Table 7.

The technologies differ in how they affect the two effects, as Table 8 summarizes. For example, energy monitoring may reveal idle loads and lower consumption, which is an efficiency effect, and the same data may reveal spare capacity that is then filled with additional orders, which is a scale effect. The net effect depends on the energy intensity of the additional output and of the output that is displaced. The black line is the break even frontier $g^* = \rho / (1 - \rho)$. Points mark the weak, moderate, and strong scenarios at $g = 4\%$.

5.3 Management Capability as the Missing Link

Smart manufacturing should not be expected to change emissions automatically. A signal must be generated and noticed, evaluated, turned into a decision, and implemented, as in Equation (10). The chain can fail at any stage: a dashboard may show an idle load that nobody owns, an analysis may recommend a change that production schedules rule out, or an implemented saving may be used to raise output. Figure 10 illustrates the compounding with assumed stage probabilities. Under dashboard monitoring alone, with $p = (0.70, 0.35, 0.50, 0.60)$, about 7% of deployments complete the chain. With analytics and alerts, $p = (0.85, 0.50, 0.60, 0.70)$ gives 17.8%, and adding closed-loop control and energy-system integration, $p = (0.90, 0.65, 0.80, 0.85)$ gives 39.8%. The values are hypothetical, but the arithmetic shows why designs that address several stages together can matter more than any single feature.

5.4 Management Capability and Energy Supply as Moderators

Management capability is likely to be an important moderator. Plants with strong energy management can act on the data that digital systems

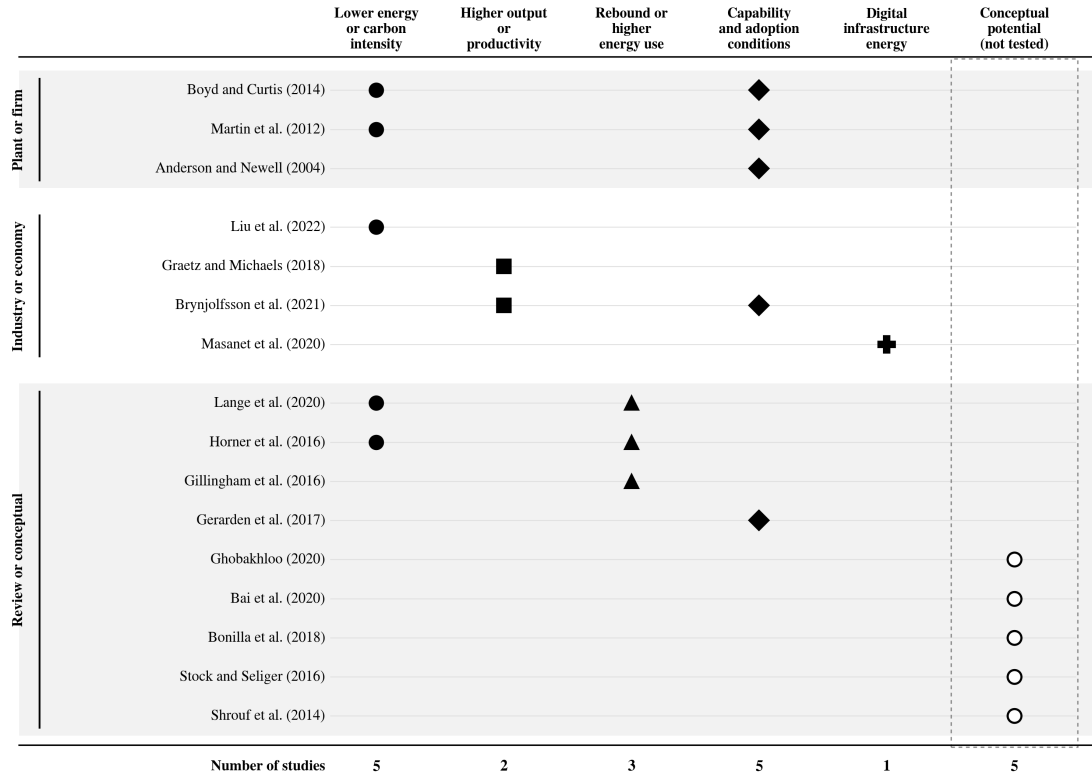


Figure 6. Findings reported in selected studies.

Table 6. Hypothetical Decomposition for One Plant ($Q^B = 1,000$, $g = 4\%$; effects on emissions in tCO_2e per period; positive means higher emissions)

Product line	s^B	s^A	e^B	e^A	f^B	f^A	Scale	Mix	Efficiency	Carbon factor	Total change
Castings and forgings	0.25	0.23	2.00	1.900	0.062	0.0608	+1.24	-2.58	-1.48	-0.56	-3.39
Machined components	0.30	0.30	1.00	0.940	0.120	0.1164	+1.44	0.00	-2.25	-1.06	-1.86
Assembled units	0.20	0.21	0.50	0.485	0.120	0.1164	+0.48	+0.62	-0.39	-0.38	+0.33
Electronics modules	0.10	0.12	0.60	0.588	0.120	0.1164	+0.29	+1.50	-0.18	-0.26	+1.34
Coated and finished goods	0.15	0.14	1.20	1.152	0.080	0.0792	+0.58	-1.00	-0.56	-0.13	-1.12
Total	1.00	1.00			$\bar{f}$: 0.1006 $\rightarrow$ 0.0922		+4.02	-1.46	-4.86	-2.40	-4.69

Line totals may not sum to the column total because of rounding.

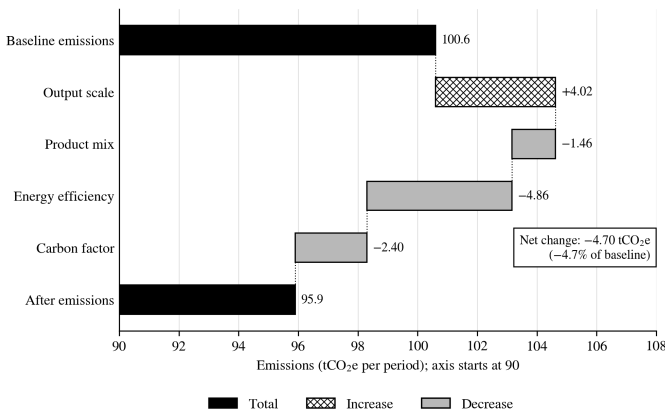


Figure 7. Waterfall of the hypothetical plant decomposition.

Table 7. Scenario Results for the Hypothetical Plant

Green shift	$\bar{f}^A$	ρ (%)	g^* (%)	NDE, $g=4\%$	NDE, $g=10\%$
None	0.1006	0.0	0.0	-4.02	-10.06
Weak	0.0976	3.0	3.1	-0.92	-6.78
Moderate	0.0922	8.3	9.1	+4.69	-0.84
Strong	0.0843	16.2	19.4	+12.94	+7.88

Scenarios multiply the mix, energy intensity, and emission factor changes of the moderate case by 0, 0.35, 1, and 2. NDE in tCO_2e per period.

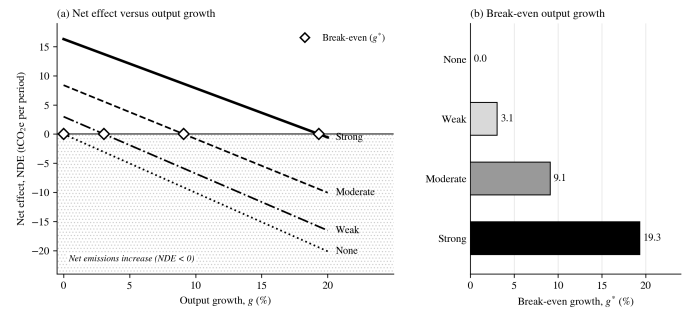


Figure 8. Net effect (NDE) of the hypothetical plant as output growth rises, for four strengths of green shift.

produce, while plants without it may use the same systems mainly to raise throughput or quality. The management and energy efficiency literature supports this interpretation (11; 31; 9). The carbon intensity of the energy supply conditions how much a given energy saving is worth in emissions terms: where electricity is carbon intensive, each unit of energy saved avoids more emissions, and where on-site or contracted low carbon supply exists, the same saving avoids less. Figure 11 illustrates the expected interaction pattern using assumed coefficients: with $\beta_1 = 3.5$ and $\beta_3 = 2.5$ in magnitude, the slope of energy intensity reduction on smart manufacturing intensity is 1.0 for low capability, 3.5 at the mean, and 6.0 for high capability, and with $\beta_1 = 3.0$ and $\beta_3 = 2.0$ for the carbon intensity of supply the slopes are 1.0, 3.0, and 5.0.

5.5 Cross Country and Sector Context

The environmental effect of smart manufacturing may vary across countries and sectors because electricity systems, energy prices, labor costs,

Table 8. Decarbonization and Output Scale Mechanisms by Smart Manufacturing Technology

Technology	Decarbonization mechanism	Output scale mechanism	Expected environmental direction
Energy monitoring and analytics	Detects idle loads and drift; supports benchmarking and targets	Reveals slack capacity that can be sold	Depends on use
Process optimization and control	Lowers energy and scrap per unit	Raises throughput and yield	Mixed
Predictive maintenance	Keeps assets at design efficiency	Raises uptime and capacity	Mixed
Digital twins and simulation	Tests lower energy schedules and designs before implementation	Speeds product launches and capacity expansion	Mixed
Energy-system integration	Shifts load, uses on-site renewables, electrifies heat	Eases energy constraints on growth	Depends on carbon factor

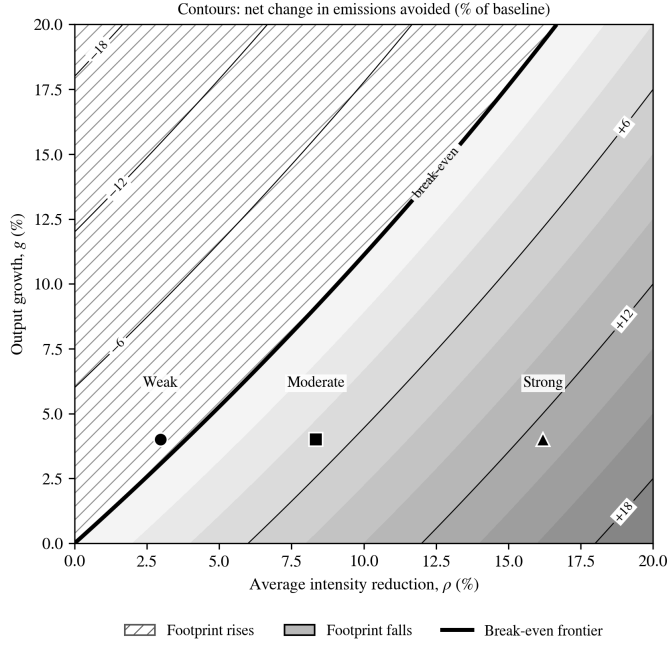


Figure 9. Sensitivity of the net emissions change to the average intensity reduction ρ and output growth g .

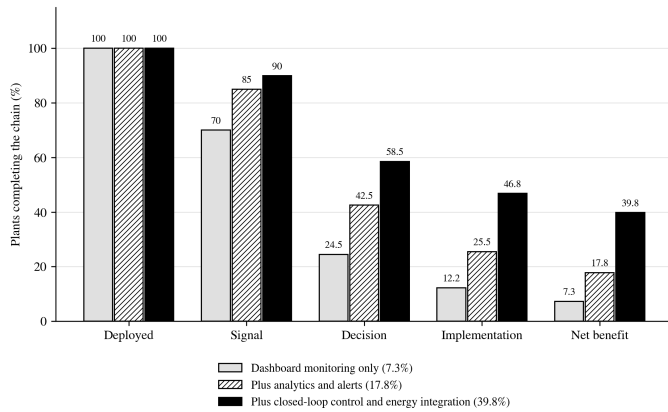


Figure 10. The organizational chain for three system designs, computed from assumed stage probabilities in Equation (10).

regulation, firm size, and digital infrastructure differ. The evidence cited here is drawn mainly from the United States, the United Kingdom, China, and cross country industry panels, and results should not be generalized automatically to Bangladesh, India, or other emerging economies, where captive generation, gas availability, grid carbon intensity, and the structure of export oriented manufacturing differ. The same system can have different consequences where the energy mix, product market, and capital constraints differ, which illustrates the need for evidence from the setting in which the policy is applied.

5.6 Research Propositions

The synthesis supports five propositions. Table 9 states each proposition with the model and expected sign used to test it, and Figure 12 maps them onto the framework.

6. Discussion

The answer to the research question depends on which technology is considered, how it is used, and how the outcome is measured. Monitoring, control, maintenance, simulation, and energy-system integration have different behavioral and technical mechanisms.

Energy monitoring can support decarbonization when it is tied to targets and owners, but monitoring without control produces information that may not change operation. Process optimization lowers energy per unit, yet it can also raise throughput. Predictive maintenance keeps assets efficient, and it also raises uptime and effective capacity. Digital twins can be used to find lower energy configurations or to accelerate growth. Energy-system integration is the channel most directly linked to the carbon factor, because it changes the carbon content of the energy used rather than only the quantity. Smart manufacturing therefore has to combine data with control, ownership, and energy supply decisions.

Decarbonization should be measured with intensity and with absolute emissions. A reduction in carbon intensity is not necessarily a reduction in total emissions, and the break even condition in Equation (8) makes this concrete: an intensity gain of a given size is beneficial only if output growth stays below the corresponding g^* . Output growth is also not a pure cost. Higher output can reflect competitiveness, employment, and welfare, so the environmental evaluation should be balanced against the economic value of the additional production (33). Absolute corporate targets and intensity targets can therefore give different answers for the same plant, and firms should state which one they are pursuing.

6.1 Managerial Implications

Manufacturers should deploy smart manufacturing together with the organizational capability to use it: named owners for energy performance, routines that turn alerts into work orders, and financing rules that fund the changes that data identify. Energy-use accounting should include the energy consumed by the digital system itself. Plant managers can track the decomposition terms separately, so that the contribution of efficiency, mix, carbon factor, and output growth is visible rather than being summarized by a single intensity ratio. Technology vendors should report realized savings from installations, with baselines and output normalization, rather than relying on engineering estimates. Lenders and investors can ask for absolute emissions together with intensity and can favor projects that couple monitoring with control and with low carbon supply. Table 10 links actions to the mechanisms they target and the indicators that show whether they work.

6.2 Policy Implications

Policy makers can encourage decarbonization through smart manufacturing by supporting energy management capability, energy audits with follow-through on recommended projects, standards for measurement and verification of savings, and access to low carbon electricity. Programs that subsidize digital adoption should be evaluated with emissions indicators as well as adoption and productivity indicators, and a program that raises output but also raises carbon intensive production may need complementary measures such as carbon pricing or sector caps. Public agencies can support data infrastructure so that plant energy, output, and emission factor data can be linked for evaluation without compromising confidentiality.

6.3 Implications for Bangladesh and Emerging Economies

Emerging economies are an important setting for future research because industrial output is expanding quickly while energy systems, in-

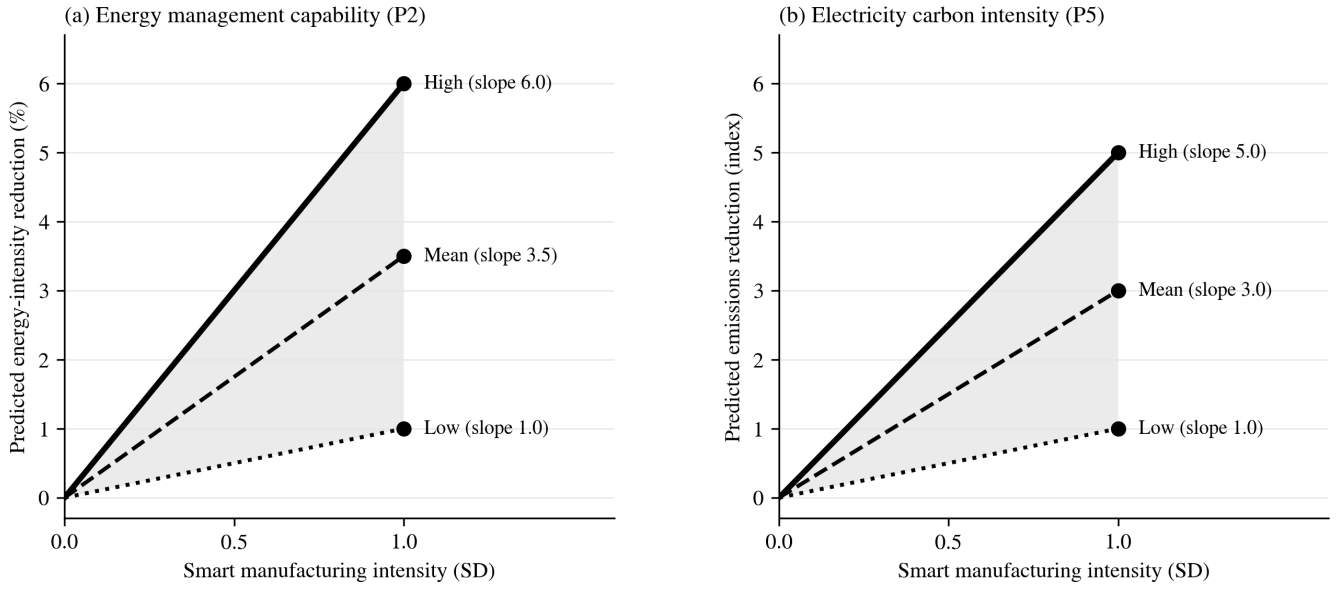
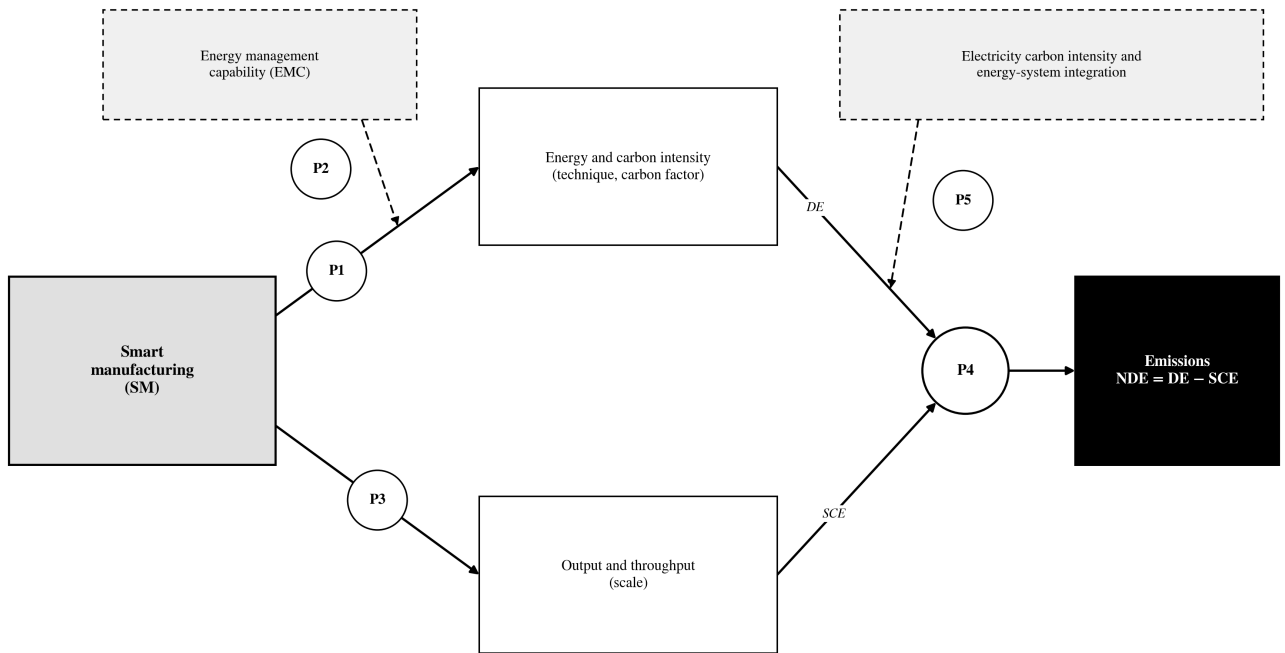


Figure 11. Simple slope plots for the moderation propositions, computed from assumed coefficients rather than estimated from data: (a) energy management capability (P2) and (b) carbon intensity of the energy supply (P5). Lines show predicted reductions at -1 , 0 , and $+1$ standard deviations of the moderator. Panel (a) plots the reduction, which is the negative of the $\ln EI$ response in Equation (15).

Table 9. Research Propositions and Their Empirical Tests

No.	Proposition	Test	Expected sign	Key data
P1	Smart manufacturing is associated with lower energy and carbon intensity of output when systems provide visibility that is linked to control and action	Eq. (13), $y = \ln EI$: α_1^{EI}	—	Plant panel of SMI and EI
P2	Energy management capability strengthens the association between smart manufacturing and intensity reduction	Eq. (15): β_3	—	SMI, EI, EMC
P3	Smart manufacturing can increase output and total energy demand through higher yield, uptime, and capacity	Eq. (13), $y = \ln Q$: α_1^Q	+	Output by line; capacity
P4	The net emissions effect depends on the relative size of the decarbonization and output scale effects	Eq. (14): sign of c ; NDE	Sign of c varies	Output, energy, emission factors
P5	Where the energy supply is more carbon intensive, the absolute emissions benefit of smart manufacturing is larger, and energy-system integration lowers the carbon factor directly	Eq. (15) with carbon factor; α_1^{CF}	—	Fuel and grid factors; load flexibility



Solid arrows: direct paths. Dashed arrows: moderating paths. P1–P5: research propositions.

Figure 12. Research propositions P1 to P5 mapped onto the framework, for future empirical testing.

frastructure, and environmental regulation change at the same time. In Bangladesh, export oriented manufacturing uses substantial energy in boilers, drying, compressed air, and captive generation, and digital monitoring and control could lower energy per unit, but the environmental effect should be tested with plant level data rather than assumed from adoption alone. A Bangladesh study could combine plant en-

ergy records, production and product mix data, emission factors for grid electricity, gas and captive generation, management capability, and the adoption of smart manufacturing, and could distinguish efficiency effects from output effects. Given the importance of the energy supply, the carbon factor term should be examined separately, and the Scope 2 method should be treated explicitly.

Table 10. Implications for Actors: Actions, Targeted Mechanisms, and Monitoring Indicators

Actor	Recommended action	Mechanism targeted	Indicator to monitor
Manufacturers	Assign owners for energy performance; link alerts to work orders; track decomposition terms separately	Capability; visibility	Share of alerts acted on; NDE and its four terms
Technology vendors	Report realized, output normalized savings with baselines	Visibility; process control	Verified saving per installation
Lenders and investors	Favor projects that couple monitoring with control and low carbon supply; request absolute and intensity emissions	Energy-system integration	Absolute emissions; carbon factor
Regulators and standards bodies	Support audits with follow-through, measurement and verification standards, and access to low carbon electricity	Capability; energy-system integration	Audit project adoption rate; Scope 2 method disclosure
Statistical agencies	Publish plant level energy and output data linkable to digital adoption	Measurement	Availability of linked data; update frequency
Researchers	Report intensity and absolute outcomes together with decomposition, break even growth, and rebound rate	Measurement	NDE; g^* ; R ; weight sensitivity of SMDI

7. Limitations and Future Research

The study has several limitations. First, it is a structured evidence synthesis rather than a new causal plant level study, and it is not a systematic review with a registered protocol. Second, direct plant level evidence on smart manufacturing and absolute emissions is limited, so the framework relies partly on adjacent literatures on digitalization, management, productivity, and rebound. Third, digital technology is measured differently across studies. Fourth, energy and emissions effects may appear with a time lag. Fifth, plant level energy data linked to digital adoption are rarely available. Sixth, the numerical illustrations are hypothetical and use assumed parameters; they demonstrate the logic of the framework and are not estimates. The classification in Figure 6 summarizes reported directions and does not weight studies by quality or sample size. Table 11 pairs each limitation with a response.

Table 11. Limitations and Proposed Responses

Limitation	Proposed response
No new causal estimate	Test P1–P5 with plant panels, staggered adoption event studies, and instruments
Thin direct evidence on absolute emissions	Collect plant level energy, output, and emission factor data
Heterogeneous digital measures	Use common core indicators and report sensitivity
Time lags	Use multi year panels and dynamic specifications
Limited linked data	Link meter, ERP, and inventory data
Illustrative numbers	Replace assumed values with estimated shares, intensities, and factors

The proposed SMDI is a measurement framework rather than a validated universal scale. Future research should validate it with confirmatory factor analysis, panel data, and observed plant records. Priority questions include how large the break even growth rate g^* is in practice for different sectors, whether control and integration deliver larger decarbonization effects than monitoring alone, how the effects differ between large firms and small and medium enterprises, how long rebound effects last, and how much energy the digital system itself consumes relative to the savings it enables.

8. Conclusion

This study examines whether smart manufacturing accelerates corporate decarbonization. The evidence indicates that the relationship is neither automatically positive nor automatically negative. Smart manufacturing can support decarbonization through energy visibility, tighter process control, reliable assets, integration with the energy system, and management capability. These mechanisms can lower energy per unit of output, shift production toward less carbon intensive lines, and lower the carbon content of the energy used. At the same time, the same technologies can raise yield, uptime, and capacity, and an output scale effect can offset the savings. Direct plant level evidence on absolute emissions is limited, and the main conclusion is therefore conditional. Smart manufacturing accelerates decarbonization when it is designed and managed to convert data into implemented savings, when it is linked to low carbon energy supply, and when output growth stays below the level that the gains can absorb. Decarbonization cannot be inferred from digitalization alone. The paper’s decomposition gives a simple test: a mix, efficiency, and carbon factor gain that lowers average carbon intensity by a proportion ρ is beneficial only if output growth stays below

$$g^* = \frac{\rho}{1 - \rho}. \quad (16)$$

The environmental effects of smart manufacturing may also vary across plants and contexts. Plants with strong energy management, clear ownership of energy performance, and access to low carbon supply may be more likely to convert digital capability into emissions reductions. In contrast, plants that use digital systems mainly to raise throughput may experience stronger scale effects. The consequences may differ across energy intensive and light manufacturing, across large firms and small and medium enterprises, and across electricity grids with different carbon intensities. Future studies should therefore avoid treating smart manufacturing as a homogeneous technology and instead examine differences across technologies, sectors, firm sizes, and energy systems.

The findings also have implications for manufacturers, technology vendors, financial institutions, and policy makers. Expanding digital adoption alone may not be sufficient to achieve decarbonization objectives. Manufacturers can pair digital systems with ownership, funding, and routines that implement the savings they identify, and vendors and lenders can emphasize verified savings and absolute emissions. Policy makers can complement digitalization programs with energy management support, measurement and verification standards, access to low carbon electricity, and carbon pricing where appropriate. Such approaches would allow the productivity benefits of smart manufacturing to be retained while directing a larger share of the gains toward emissions reductions rather than additional output.

An additional consideration is the rebound effect. Efficiency improvements enabled by digital technologies may reduce the energy intensity of production while lowering effective costs or raising capacity. Consequently, a reduction in emissions per unit of output does not necessarily translate into a reduction in total emissions, and the rebound rate in Equation (9) shows how quickly savings can be consumed: with an 8% intensity gain, 4% growth offsets 46% of the engineering saving and 10% growth offsets more than all of it. Evaluating smart manufacturing therefore requires both intensity based and absolute indicators, together with the energy used by the digital system itself.

There are also important limitations to the available evidence. Much of the existing literature relies on conceptual analyses, observational data, or aggregate measures of digitalization and environmental outcomes. These approaches can identify associations and potential but may not fully establish the causal mechanisms connecting digital adoption, production decisions, and plant emissions. Differences in the measurement of digitalization, energy efficiency, and corporate emissions also make direct comparison across studies difficult. Moreover, rapid changes in industrial artificial intelligence, edge computing, and energy management software mean that findings from earlier periods may not fully represent current manufacturing environments.

Future empirical research should therefore test the framework with plant panel data, meter level energy data, output and product mix records, management capability measures, and emission factors. Where possible, researchers should distinguish between digital systems that are used for control and energy-system integration and those that primarily support throughput. Natural experiments, staggered roll outs, and longitudinal plant surveys could further help identify causal effects and reveal whether efficiency gains persist over time. Research could also examine how management capability and energy supply interact with digital capability.

Overall, the environmental consequences of smart manufacturing depend not only on how much production becomes digital, but also on how digitalization shapes the mix, intensity, carbon content, and scale

of production. The central policy and research question is therefore not whether smart manufacturing is inherently green, but under what organizational, technological, and energy-system conditions its benefits can outweigh its output-expanding effects. The paper's framework provides a basis for making this distinction and for identifying when smart manufacturing becomes an enabler of corporate decarbonization and when it becomes a mechanism for additional output.

Data Availability

No new primary dataset was collected for this evidence synthesis. The paper is designed to support future empirical testing with plant level energy and production data, emission factors, and management surveys. The code used to produce the illustrative figures and numerical example (`make_figures.py`) is available from the authors on request.

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