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RESEARCH

Industrial energy use, efficiency, and savings: methods for quantitative analysis

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Abstract Evaluating energy efficiency (EE) in the manufacturing sector at the national level is analytically challenging due to the sector's heterogeneity and the limitations of commonly used indicators. Despite manufacturing's central role in industrial decarbonization, there is no comprehensive overview of the quantitative methods used to assess its EE. This study addresses this gap by systematically reviewing 110 peer-reviewed studies published between 2005 and 2024, focusing on the evolution, application, and reliability of ratio-based indicators, decomposition techniques (Index and Structural Decomposition Analysis), frontier methods (Data Envelopment and Stochastic Frontier Analysis), and econometric approaches. The review reveals a strong preference for econometric analysis, followed by ratio indicators and index decomposition, while frontier and structural decomposition techniques remain underused. We identify four key challenges that can affect the robustness of EE assessments: definition inconsistencies in conceptualizing EE, data limitations affecting disaggregation and comparability, potential misalignment between methods and data, and interpretation challenges when translating findings into policy insights. Our systematic assessment indicates that most studies fall short of good methodological practices, with ratio-based methods performing strongest overall, suggesting that robust EE assessment requires (a) methods aligned with specific contexts, (b) sufficiently disaggregated data, and (c) awareness of methodological limitations. This review offers a framework for addressing methodological challenges in manufacturing EE analysis, improving the reliability of information available to policymakers for effective EE interventions.

Keywords Energy efficiency measurement · Manufacturing sector · Sectoral heterogeneity

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Introduction

Industrial energy efficiency (EE) is key policy objective due to its benefits for economic competitiveness, energy security, and environmental sustainability. Manufacturing, accounting for approximately 95% of total industrial energy consumption in the European Union (Odyssee-Mure…, 2023), plays a particularly significant role in this context. As a key driver of economic activity contributing substantially to GDP, employment, and trade across Europe, the manufacturing sector is increasingly considered in EE policies, such as the Energy Efficiency Directive and the Emissions Trading System.

Measuring and evaluating EE in manufacturing presents unique analytical challenge compared

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to other sectors. Manufacturing covers 232 NACE classes (C10–C33) – far more than other industries such as mining, electricity, or water supply (38 classes combined) or transport (30 classes). This exceptional diversity reflects a wide range of production processes, energy intensities, materials, and products, which complicates meaningful aggregation and comparison (Bosseboeuf et al., 1997; Freeman et al., 1997; Tanaka, 2011). Unlike other industries or transport, where energy use patterns are more uniform, manufacturing requires a more nuanced approach to analysing EE trends and identifying areas for improvement.

Beyond sectoral heterogeneity, the nature of EE itself introduces additional complexities. EE is inherently relative and context-dependent (Ang, 2006; Patterson, 1996). It becomes meaningful only when compared against benchmarks like historical data, peer performance, or predefined thresholds. While measuring EE is straightforward at equipment or plant level (e.g., using Best Available Technology benchmarks), country-level assessment is challenging without clear reference points or comparable facilities. At this macro level, isolating technical efficiency from influences like production structure or operational practices remains a major hurdle (Berndt, 1978; Phylipsen et al., 1997).

Ideally, EE should be assessed using physical indicators (e.g., energy consumption per ton of steel), as these reflect actual process-level efficiency (Patterson, 1996). However, due to data constraints and the need for cross-sector comparisons, economic indicators such as energy intensity (energy use per unit of GDP or value-added) are often used instead. These indicators are influenced by price fluctuations, structural changes, and economic cycles (Filippini & Hunt, 2015; Pérez-Lombard et al., 2013), complicating the extraction of technical efficiency improvements that policymakers need to evaluate. Without proper methods to separate these non-technical effects, observed trends may reflect economic or structural changes rather than genuine efficiency gains.

Various initiatives by the IEA (2014, 2021), ODYSSEE-MURE (Enerdata, 2020), OECD (1997), World Energy Council (2008, 2016), as well as U.S. Department of Energy (McNeil et al., 2016) address these challenges, yet Zazzera et al. (2025), the IEA (2014), McWilliams, Tagliapietra, and Zachmann (2025) highlight persistent disconnects between policy ambitions and actionable data.

Early research relied on ratio-based economic indicators like energy intensity due to their simplicity, but these often fail to capture true efficiency improvements (Phylipsen et al., 1997). More recent studies have adopted advanced methods like Index Decomposition or Data Envelopment Analysis (Ang & Liu, 2001; Zhou & Ang, 2008), though their reliability remains dependent on data quality and specificity (Pérez-Lombard et al., 2013).

This paper addresses two key research questions:

- What methods are used for country-level evaluation of EE in manufacturing, and how have these evolved over time?
- How do data choices and methodological design affect the reliability and validity of EE assessments?

To answer these questions, we first address the challenges of measuring EE in the manufacturing sector (Introduction). Next, we identify main methods used to study EE in manufacturing (Methodology). These methods and their applications are then presented in an overview format (Results). Finally, we discuss methodological limitations and propose strategies to mitigate associated risks (Discussions).

Unlike earlier reviews that focused on ratio-based indicators (Freeman et al., 1997; Patterson, 1996; Pérez-Lombard et al., 2013) or more recent studies that examined single methods such as Index Decomposition or Data Envelopment Analysis, no comprehensive review compares multiple approaches and their limitations in manufacturing EE analysis.

This paper fills that gap by assessing ratio methods, decomposition techniques, frontier methods and other econometric approaches, analysing their applications and challenges. A key objective is to provide guidance for policymakers by addressing these risks and improving the reliability of EE assessments.

Methodology

This study systematically reviews quantitative methods used to measure EE in the manufacturing sector at the country level over the last two decades (2005–2024), focusing on Index Decomposition

Analysis (IDA), Structural Decomposition Analysis (SDA), Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and related approaches. This review examines both the theory behind these methods and their empirical applications to evaluate how these methods are used to capture EE trends and support policy decisions. A structured Scopus search yielded 7,229 articles, from which a final set of relevant studies (n = 110) was selected based on predefined criteria (Annex 1). Key data were extracted for comparative analysis, and methodological rigor was evaluated across several dimensions.

The number of articles published doubled from 14 (2005–2009) to 29 (2010–2014), then remained relatively stable with 32 (2015–2019) and 35 (2020–2024), indicating growing interest that has recently plateaued (Fig. 1). Methodological preferences have evolved significantly: IDA peaked in 2010–2014 before declining, while econometric methods became dominant in recent years. Ratio-based approaches decreased as DEA surged in 2020–2024, reflecting greater interest in EE benchmarking. Both SDA and SFA remained minimal throughout. Other methods showed variable usage, with the most recent period (2020–2024) marked by the emergence of machine learning and AI-based models, signalling a shift toward more data-driven analytical approaches.

Of the 110 studies reviewed, the majority focus on one or two countries (74), with China (25) and Germany (6) being most frequently analyzed. Over the review period, roughly one-third of the studies focused on energy-intensive industries (e.g., steel, cement), about one-sixth on less energy-intensive sectors (e.g., textiles, food), and nearly half adopted a general or mixed-sector perspective. The emphasis on intensive sectors was strongest during 2010–2014, accounting for almost half of the studies at that time, but dropped to around one-fifth by 2020–2024. In contrast, studies on less intensive sectors grew modestly. This recent period also reflects a diversification of methods, with increasing use of econometric models and DEA alongside traditional decomposition techniques.

In addition to mapping methods and trends, we assessed each reviewed study against three critical parameters aligned with the challenges outlined in the introduction. Each study was evaluated as meeting or not meeting the threshold for good practice in each criterion:

Definition consistency—whether the study demonstrates awareness of conceptual challenges in defining energy efficiency at the sectoral level, particularly that heterogeneity in production processes, product mixes, feedstock quality, and system boundaries affects the interpretation of efficiency metrics. Studies met this threshold if they acknowledged at least some of these complexities and their impact on measurement validity.

Data granularity—whether the level of sectoral disaggregation and the use of physical versus economic indicators adequately reflects manufacturing's technological and product diversity. This was rated positively when studies used detailed sectoral disaggregation (typically 3-digit, or 4-digit for highly heterogeneous sectors such as food and beverages), process-level data, or physical output indicators rather than relying solely on aggregate economic metrics.

Method-context alignment—whether the analytical approach accounts for heterogeneity in

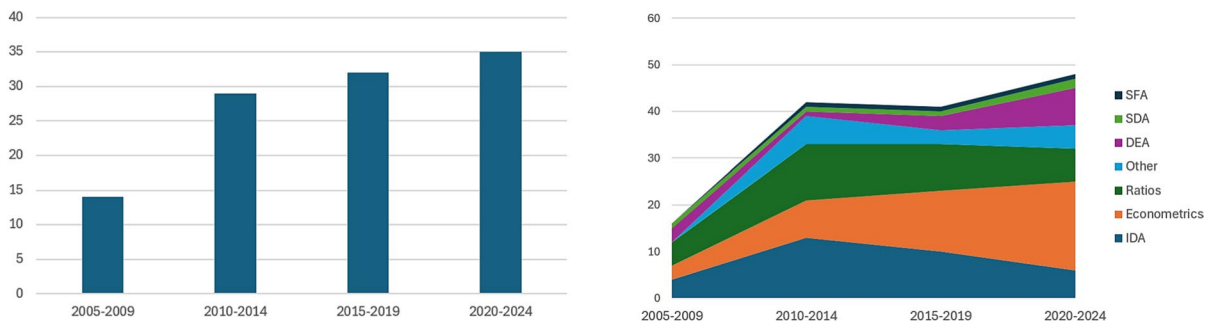

Fig. 1 Number of articles and trends in methodological approaches for EE analysis in manufacturing industry (2005–2024)

industrial structure and whether it is applied in a way that reflects industrial diversity. Studies were assessed positively when the approach was adapted to reflect manufacturing diversity—for example, by using sector-specific parameters, including variables to control for industrial heterogeneity, or incorporating physical production characteristics.

This structured evaluation reveals how methodological risks emerge across different approaches and enables systematic comparison of practices across the literature.

Results

Measuring EE in manufacturing is methodologically challenging due to the interplay of technical, structural, and economic factors. A variety of methods have been developed, each with its own strengths and limitations. These range from single-factor approaches focused on energy inputs (Patterson, 1996) to total-factor models incorporating capital and labor (Hu & Wang, 2006). Methodologically, they include non-parametric techniques without specific functional forms and parametric approaches requiring predefined functions (Filippini & Zhang, 2016). Figure 2 categorizes these methods by input consideration and analytical framework.

The main methodological approaches distinguished within this review are:

Ratio-based method—simple indicators comparing energy consumption to output, providing straightforward but often limited insights into efficiency trends.

Decomposition analysis—techniques that disaggregate energy consumption or intensity changes into contributing factors such as activity effects, structural changes, and efficiency improvements. These include Index Decomposition Analysis (IDA) operating on sectoral data and Structural Decomposition Analysis (SDA) utilizing input-output frameworks.

Data Envelopment Analysis (DEA)—a non-parametric frontier approach that identifies efficient production frontiers through linear programming, capable of handling multiple inputs and outputs without assuming specific functional relationships.

Stochastic Frontier Analysis (SFA)—a parametric econometric technique that estimates efficiency frontiers while distinguishing between inefficiency and random statistical noise.

Other econometric methods—diverse analytical techniques including panel data models, vector autoregression (VAR), vector error correction models (VECM), and convergence analysis, which examine relationships between EE and its determinants while accounting for complex interactions and time-series dynamics.

Each method offers different perspectives on EE, with trade-offs between simplicity, data requirements, and analytical depth. As shown in Fig. 2, the methods

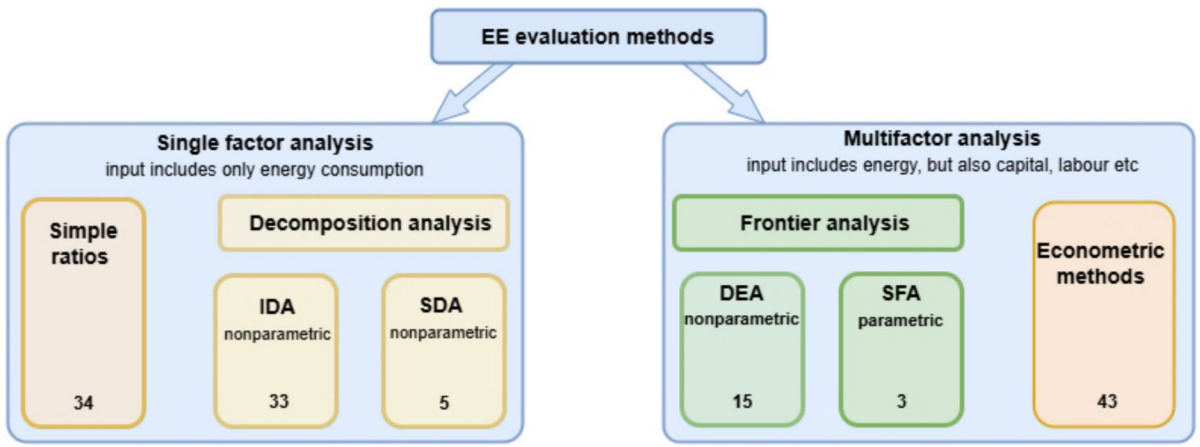

Fig. 2 Categorization of energy efficiency evaluation methods in manufacturing and their application frequency

range from relatively simple single-factor approaches to more complex multifactor techniques. The selection of appropriate methods depends on data availability, sectoral characteristics, and specific research objectives (Zhou & Ang, 2008).

The following sections examine each methodological approach systematically. For each method, we first provide a description of the technique and its theoretical foundations, then analyze its application in the reviewed studies, and finally present our assessment against the three criteria—definition consistency, data granularity, and method-context alignment—outlined in the methodology. This structured approach enables systematic comparison across different techniques and identification of best practices, which are summarized in Table 1.

Ratio-based approach

EE refers to using less energy to produce the same service or useful output (Patterson, 1996). In the context of manufacturing, this typically implies improvements in the technical performance of energy-using systems—achieved through more efficient technologies, optimized processes, or reduced energy losses. Ratios are among the oldest and most intuitive methods for quantifying EE. They measure energy consumption relative to an output or activity metric, such as energy use per unit of physical output (e.g., kWh per ton of steel) or economic output (e.g., MJ per EUR of GDP). Based on the variables used in the numerator and denominator, ratio methods can be classified into several categories (Patterson, 1996). Their simplicity, transparency, and ease of interpretation make them widely used for benchmarking, policy reporting, and cross-country or cross-sector comparisons. However, ratio indicators often cannot distinguish between changes driven by technical efficiency improvements and those resulting from structural shifts, product mix changes, or external factors such as climate or economic fluctuations.

Energy Intensity (EI) is the most widely used ratio metric, expressing the energy required to produce one unit of economic output. It is typically interpreted inversely as a measure of EE—lower intensity implies higher efficiency (Phylipsen et al., 1997). The closer the analysis is to the process or equipment level, the more accurately EI reflects actual energy efficiency, as structural and economic distortions are minimized.

Energy Productivity (EP), mathematical inverse of EI, represents the economic output generated per unit of energy consumed. While energy productivity and EE are sometimes used interchangeably in literature and policy documents, they reflect different conceptual framings:

> Energy efficiency (EE) refers to technical efficiency and is typically a normative concept, aim-

Table 1 Performance of EE studies against assessment criteria

Method	Studies (n)	Definition consistency	Data granularity	Method-context alignment	Notable examples
Ratio methods	34	21 (62%)	17 (50%)	15 (44%)	Lipiäinen et al. (2022); Bruni et al. (2021); Rojas-Cardenas et al. (2017); Gutowski et al. (2013); Cahill and Gallachoir (2012); Oda et al. (2012); Saygin et al. (2012); Xu et al. (2009); Neelis et al. (2007); Ramirez, Patel, and Blok (2006b)
IDA	33	12 (36%)	5 (15%)	6 (18%)	Lipiäinen et al. (2022); Norman (2017); Cahill and Gallachóir (2012); Fracaro et al. (2012); Xu et al. (2012); Sheinbaum et al. (2010)
SDA	5	0 (0%)	0 (0%)	0 (0%)	None identified
DEA	15	7 (47%)	3 (20%)	2 (13%)	Azadeh et al., (2007, 2008)
SFA	3	0 (0%)	0 (0%)	0 (0%)	None identified
Other econometric methods	43	10 (23%)	2 (6%)	2 (6%)	Costantini et al. (2024); Bruni et al. (2021)

ing for improvement—using less energy for the same output.

Energy productivity (EP) describes the economic value generated per unit of energy and is a more descriptive measure, reflecting output performance rather than technical change. From a methodological perspective, researchers should be aware of this terminological overlap while recognizing that the choice between "efficiency" and "productivity" framing may influence how findings are interpreted by different stakeholders.

Energy Efficiency Index (EEI) compares actual energy use to a reference or best practice level. Values below 100 indicate better-than-reference performance, while values above 100 suggest higher consumption (Saygin et al., 2011):

$$EEI = \frac{ActualEnergyConsumption}{ReferenceEnergyConsumption} \times 100$$

Specific Energy Consumption (SEC) measures energy use per unit of physical output and is especially useful in industries with homogeneous products, such as cement, steel, or paper (Worrell et al., 2001). It has been applied in national studies to assess efficiency potential:

$$SEC = \frac{EnergyConsumption}{PhysicalProduction}$$

While ratio methods are limited in their ability to separate technical efficiency improvements from structural or external factors, they remain fundamental in energy analysis. When detailed data are available—especially at the process or product level—ratios such as Specific Energy Consumption (SEC) can offer valuable insights. In broader applications, ratio indicators like Energy Intensity (EI) may lack explanatory power on their own but still serve as key inputs in decomposition or econometric models, maintaining relevance within more advanced methodological frameworks (Bosseboeuf et al., 1997; McNeil et al., 2016).

Based on how ratio indicators are used, this review groups 34 studies into three categories:

Ratio-only studies (18) use EI, SEC or EEI to track trends or compare sectors (e.g., Bruni et al., 2021; Rojas-Cardenas et al., 2017; Xu et al., 2009; Neelis et al., 2007; Ramirez, Patel, and Blok 2006a; Ramirez, Patel, and Blok 2006b). Most studies rely on physical output units to calculate energy efficiency, while only a few use economic metrics to quantify production outcomes (e.g., Pappasa et al., 2018; Edelenbosch et al., 2017; Dudzevičiute, 2013).

Combined-method studies (9) integrate ratios with decomposition, frontier, or econometric methods to identify the drivers of energy efficiency, separate efficiency effects from structural changes, benchmark other methods against ratio indicators, and account for external influences. (e.g., Lipiäinen et al., 2022; Li, Li, and Wang 2021; Peng et al., 2015; Pardo Martınez, 2011).

Supportive-role studies (7) apply ratio indicators as secondary variables within broader models—such as IDA, convergence, or policy simulations— mainly to descriptively outline historical trends, compare sectors or countries, and set the stage for deeper analysis (e.g., Enevoldsen et al., 2007; Lin & Xie, 2015; Miketa & Mulder, 2005). They helped contextualize the research but were not used to draw causal conclusions, which instead relied on decomposition, econometric, or scenario-based methods.

This distribution shows that ratio methods serve diverse analytical purposes, with half the studies (50%) relying on ratios as primary indicators, while the remainder use them either as complementary tools within multi-method approaches (26%) or as contextual background for more complex analyses (21%).

Beyond usage patterns, we also evaluated how well these ratio-based studies addressed methodological challenges. Assessment of the 34 ratio-based studies shows mixed performance against the three criteria. **Definition consistency** was relatively strong, with about two-thirds of studies clearly distinguishing energy efficiency from energy intensity and stating their scope explicitly. **Data granularity** was adequate in half the studies, which used 4-digit sectoral resolution or process-level data and relied primarily on physical output measures rather than economic indicators. Notable examples include detailed process-level analyses in petroleum refining (Han et al., 2015), plant-level studies in food processing (Xu et al., 2009; Ramirez, Patel, and Blok, 2006b), and cement

industry audits (Bruni et al., 2021). **Method-context alignment** was weaker, with 44% of studies (15/34) meeting this criterion, as some focused on energy use tracking rather than efficiency measurement per se. Several studies demonstrated strong performance across all criteria through their technical focus, use of physical data, and clear sector boundaries (in addition to studies mentioned above, see Lipiäinen et al., 2022; Rojas-Cardenas et al., 2017; Gutowski et al., 2013; Cahill and Gallachoir, 2012; Oda et al., 2012; Saygin et al., 2012).

Decomposition methods: index-based and structural approach

Decomposition analysis disaggregates changes in energy consumption or intensity into multiple factors, revealing the drivers behind observed trends. Two primary approaches are Index Decomposition Analysis (IDA) and Structural Decomposition Analysis (SDA). While both aim to isolate effects such as activity, structural, and intensity change, IDA—due to its lighter data requirements—is more widely used in industrial EE research (33 studies), whereas SDA is applied in only 5 reviewed cases.

IDA originates from index number theory, initially developed to decompose changes in prices and economic output. It uses aggregated sector-level data, making it suitable for time series analysis with annual data. IDA can be applied in additive (absolute change) or multiplicative (relative change) form:

$$\Delta E = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} \text{or} \frac{E^T}{E^0} = \Delta E_{act} \times \Delta E_{str} \times \Delta E_{int}$$

where ΔE is the total change in energy consumption between the base year and target year, ΔE_{act} is the activity effect (economic growth), ΔE_{str} is the structural effect (sectoral shifts), ΔE_{int} is the intensity effect (efficiency improvements), and $\frac{E^T}{E^0}$ expresses the relative change in total energy consumption between the target year (T) and base year (0).

The most common IDA method is Logarithmic Mean Divisia Index (LMDI), which ensures perfect decomposition with no residuals (Ang, 2004). Earlier indices like Laspeyres and Paasche often produced residuals that hindered interpretation. IDA can handle various indicator types (e.g., absolute energy use, intensity, or elasticity), and zero values pose minimal problems compared to SDA.

SDA, rooted in input–output economics, models inter-sectoral relationships through input–output tables, capturing how changes in one sector propagate throughout the economy (Rose & Casler, 1996; Hoekstra et al., 2003). It is more data-intensive and might employ 3–5-year intervals due to the infrequent construction of input–output tables.

While decomposition methods reduce the risk of misattributing observed changes in energy use to efficiency improvements, they cannot fully eliminate it. The intensity effect (ΔE_{int}), often interpreted as a proxy for technical EE, may also reflect structural shifts, operational changes, capacity utilization, or unobserved heterogeneity—especially when data granularity is limited. The accuracy of factor attribution depends on the disaggregation level and data quality.

Among reviewed studies, LMDI dominates due to its flexibility, theoretical robustness, and compatibility with national statistics. About 60% of studies apply the standard three-effect decomposition: activity, structure, and intensity (e.g., Jain, 2023; Lipiäinen et al., 2022; Duran et al., 2015; Cahill and Gallachoir, 2012; Fracaro et al., 2012). Some studies, however, omit or combine effects, using only two components—typically structure and intensity (e.g., Parker & Liddle, 2016; Unander, 2007; Zakari et al., 2021). Others extend the framework by adding factors such as innovation intensity, or capital investment patterns (e.g.,Lin & Long, 2014; Wang et al., 2018; Xu et al., 2012).

Multiplicative LMDI is preferred in studies focusing on relative contributions of energy consumption drivers (Olanrewaju, 2019; Voigt et al., 2014; Wang et al., 2018), while additive LMDI is used where total impact attribution is required (Duran et al., 2015; Sheinbaum-Pardo et al., 2012; Zaekhan et al., 2022).

A few studies apply alternative indices such as Fisher Ideal or Paasche method (e.g., Cahill & Gallachóir, 2012; Moshiri & Duah, 2016; Zakari et al., 2021), and some combine LMDI with econometric models to explore causal or convergence mechanisms (e.g., Löschel et al., 2015; Pardo Martinez, 2010; Mulder, 2015).

Data quality remains a limiting factor, particularly in developing economies. While developed countries offer detailed energy statistics, many studies highlight the need for improved data collection and

harmonization to enable robust decomposition (e.g., Jain, 2023; Sheinbaum-Pardo et al., 2012; Wang et al., 2017).

SDA is applied in a few cases, mostly for broader macroeconomic assessments (e.g., Wachsmann et al., 2009; Zeng et al., 2014; Yang, Xu, and Su, 2022). Only two studies focus specifically on manufacturing-related energy use (Huang et al., 2017; Zhu et al., 2020).

Assessment of IDA studies (n = 33) reveals mixed methodological performance. About one-third demonstrated good **definition consistency**, acknowledging that energy intensity may not reflect technical EE and discussing issues like product mix or input differences. **Data granularity** was limited, with most studies using 2-digit economic data rather than physical output indicators. Some studies enhanced their analysis using the ODYSSEE-ODEX dataset (Odyssee database, 2025; Lapillonne, 2020), which includes physical output indicators (e.g., Cahill & Gallachóir, 2012; Pusnik et al., 2017). Several studies stood out through their use of physical indicators or bottom-up disaggregation (Fracaro et al., 2012; Lipiäinen et al., 2022; Norman, 2017; Xu et al., 2012). **Method-context alignment** was weak, with less than 20% of studies adjusting their approach to reflect industrial diversity. The majority applied standard decomposition (typically 2–3 factors) without considering intra-sector differences or non-technical drivers that may be captured in the intensity effect.

SDA studies (n = 5) showed limited performance across all criteria, with none addressing data granularity, sectoral heterogeneity, or energy efficiency definition issues.

Frontier analysis: data envelopment analysis (DEA)

Frontier analysis, a benchmarking approach, measures efficiency by comparing homogeneous decision-making units (DMUs—firms, sectors, or countries) to an estimated"best-practice"frontier. Two main approaches are used: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). These methods estimate technical efficiency, but differ in their methodological foundations—DEA is non-parametric and does not require a functional form, while SFA is parametric and distinguishes inefficiency from statistical noise. Unlike micro-level benchmarking applications, national or sector-level EE studies often rely on aggregate data, making the assumption of homogeneity across units problematic. However, these methods can still provide valuable insights when applied carefully, with attention to sectoral structure and technological diversity.

Rooted in Farrell's (1957) concept of technical efficiency, DEA employs linear programming to construct an efficiency frontier that evaluates each decision-making unit (DMU) against its most efficient counterparts. This method allows for multiple inputs and outputs, effectively addressing the complexities of industrial energy consumption. DEA can integrate factor substitution dynamics and incorporate contextual variables that influence energy consumption but lie beyond the DMU's control (Boyd, 2008; Filippini & Hunt, 2015).

DEA has been widely applied in EE assessment, with reviews covering both theoretical advancements (Emrouznejad & Yang, 2018; Cook & Seiford, 2009; Liu, Lu, and Lu, 2016) and energy-specific applications (Mardani et al., 2017; Sueyoshi et al., 2017; Toloo et al., 2021; Xu et al., 2020). Extensive literature covers DEA applications, theory, models, and software (Cooper, Seiford, and Zhu, 2011; Ramanathan, 2003), with numerous model extensions enhancing its applicability to manufacturing EE contexts.

Over decades, Data Envelopment Analysis (DEA) has evolved significantly, incorporating various methodological extensions to account for scale efficiency, technological heterogeneity, time variation, and environmental factors. The CCR model (Charnes et al., 1978) and BCC model (Banker et al., 1984) mark the beginning of DEA, introducing constant and variable returns to scale respectively.

To capture performance changes over time, DEA has been extended with dynamic models. The Malmquist Energy Productivity Index (MEPI), based on the Malmquist Productivity Index (MPI), is tailored for energy-focused analysis. It treats energy as a distinct input and decomposes productivity efficiency change (catching up to the best practice) and technological change (frontier shift), enabling time-based assessment of energy performance.

Metafrontier DEA (Battese & Rao, 2002; Battese, Rao, and O'Donnel, 2004) allows comparison across heterogeneous groups by estimating group-specific

frontiers and a global metafrontier, making it particularly suitable for assessing technological gaps in diverse manufacturing systems.

Total Factor Energy Efficiency (TFEE), proposed by Hu and Wang (2006), adds an energy-focused perspective by measuring the ratio of optimal to actual energy use, holding other inputs and outputs constant—offering a direct indicator of energy-saving potential.

DEA was used in 15 reviewed studies to evaluate industrial EE. Applications ranged from national and regional assessments to sector-specific analyses, including non-ferrous metal (Lin & Chen, 2020), pulp and paper (Lin & Zheng, 2017), and textiles (Lin & Bai, 2020; Zhao & Lin, 2020). Several studies combined DEA with econometric models, such as Tobit regression (Zhao & Lin, 2020; Pardo Martínez, 2009, 2011), to identify influencing factors. Around half of the reviewed studies focused on China (e.g., Dong et al., 2021; Li et al., 2022; Lin & Bai, 2020). Although metafrontier DEA offers strong potential for addressing technological heterogeneity—particularly across diverse industrial subsectors—it was applied in only two of the reviewed studies, and both focused exclusively on regional differences (Lin & Bai, 2020; Lin & Zheng, 2017). This limited application is likely due to the lack of disaggregated data on inputs, outputs, or technologies at the subsector level.

To assess how well DEA studies addressed methodological challenges, we evaluated all 15 studies against the three criteria. **Definition consistency** was relatively strong, with nearly half the studies explicitly distinguishing energy efficiency from related concepts and acknowledging sectoral complexity and diversity. **Data granularity** was limited, as only 20% used disaggregated data while most relied on 2-digit economic indicators, addressing diversity through geographic rather than technological disaggregation. **Method-context alignment** was weakest, with only 13% adapting DEA models to manufacturing-specific characteristics despite often acknowledging sectoral complexity. Some studies included descriptive data to illustrate diversity without incorporating it into the DEA framework (e.g., Lin & Bai, 2020). Azadeh et al. (2007) and Azadeh et al. (2008) stand out for combining at least 3-digit data with an appreciation of industrial diversity.

Frontier analysis: stochastic frontier analysis (SFA)

SFA is a parametric method that estimates a production or energy frontier by specifying a functional form (e.g., Cobb–Douglas, Translog) and separating deviations into inefficiency and random noise (Aigner et al., 1977; Meeusen and Van den Broeck, 1977). This makes SFA particularly useful in studies with external shocks or measurement uncertainty.

Only three reviewed studies applied SFA to assess manufacturing EE. Hu and Honma (2014) analyzed sectoral efficiency across OECD countries; Gamtessa and Childs (2019) investigated short-term inefficiency in Canadian industry; and Yang et al. (2024) conducted a firm-level study covering 191,615 enterprises in China.

To evaluate the methodological approach of these SFA applications, we assessed all three studies against the criteria. Assessment shows weak performance across all three areas. **Definition consistency** was limited—while all studies aimed to measure energy efficiency, none addressed conceptual challenges such as manufacturing complexity or sectoral boundaries. **Data granularity** was poor: two used 2-digit economic data, including one at the firm level, but none accounted for process or product variation. **Method-context alignment** was also weak, with no study adapting the SFA approach to reflect manufacturing-specific characteristics. As a result, none of the studies met the thresholds for any of the three criteria.

Other econometric methods

The study of EE relies on a variety of econometric techniques, each designed to address specific research questions, data structures, and potential econometric issues such as endogeneity, heterogeneity, and dynamic relationships.

Panel regression is the most widely applied approach (13 studies), used to study how economic and technological factors influence EE over time. Several studies use **fixed effects models** to control for unobserved heterogeneity across industries and regions. For example, Matthess et al. (2023) find that robot density reduces energy intensity in European manufacturing, while investment in digital capital — including ICT equipment and automation technologies — may increase it due to rebound effects or energy-intensive deployment. Sahu et al. (2024)

show that in Indian chemical firms, larger firm size and investment in technology lower energy intensity, whereas outdated equipment and low labor productivity raise it.

Generalized Method of Moments (GMM) is used to estimate dynamic panel data models where endogeneity is a concern. GMM was used in 4 studies to estimate dynamic relationships, such as the effect of past EE, automation, or investment patterns (e.g., Wang, Lee and Li, 2022).

Vector autoregression (VAR) and vector error correction models (VECM) (6 studies) are dynamic econometric techniques used to analyze interdependencies among multiple time series variables. In a VAR model, each variable is modeled as a linear function of its own past values and those of other variables in the system, assuming the data are stationary. When variables are non-stationary but cointegrated, VECM extends VAR by incorporating error correction terms, which capture the speed at which deviations from the long-run equilibrium are corrected in the short run. Zakari et al. (2021) used VECM to demonstrate how economic growth and industrial investment positively impact Nigeria's EE, while Li et al. (2017) applied VAR modeling within a Wuli–Shili-Renli (WSR) framework to identify key determinants of China's manufacturing energy intensity. Lin and Long (2014), Lin and Xie (2015), and Lin et al. (2017) employed cointegration and error correction methodologies to analyze energy conservation potential in China's chemical, petroleum refining, and cement industries respectively, consistently finding that R&D investment and technological improvements are the most significant factors for reducing energy intensity, while energy prices show limited impact due to government regulation and subsidies.

Censored and discrete choice models (9 studies) are used to estimate EE outcomes when dependent variables are either bounded or binary. Tobit regression models are particularly useful when analyzing efficiency scores—often derived from DEA—that have upper or lower limits. Logit models effectively address binary EE investment decisions. Logit models have examined diverse factors affecting EE investments, with education level of R&D staff, cooperation with research institutions and competitors, and company size emerging as significant positive drivers (Ozbugday et al., 2022; Solnørdal & Thyholdt, 2017). Tobit models were used to analyze bounded EE scores and their determinants, including trade, regulation, and investment (Pardo Martínez, 2011; Shi et al., 2021). Zhao and Lin (2020) extended this approach with a simultaneous equations model to explore the two-way relationship between trade and EE in China's textile sector.

Convergence analysis (6 studies) examines whether EE gaps between countries or sectors narrow over time. Two main approaches are used: beta-convergence (measuring catch-up rates) and sigma-convergence (measuring dispersion reduction). Mulder and de Groot (2012) and Lin and Zheng (2017) applied beta-convergence models to show that less efficient sectors gradually catch up to leaders. Sigma convergence studies by Miketa and Mulder (2005) tracked 56 countries across 10 manufacturing sectors over 25 years, finding that differences narrowed most significantly in less energy-intensive industries. Mulder and de Groot (2012) found similar patterns across 18 OECD countries from 1970 to 2005, with convergence accelerating after 1995. Parker and Liddle (2017) identified distinct regional"clubs"of countries with similar convergence patterns.

To evaluate the methodological approach of econometric studies, all 43 studies were assessed against the three criteria. Assessment reveals generally weak alignment across all areas. **Definition consistency** was limited, with only about one-quarter demonstrating good performance, while many studies blurred the distinction between energy efficiency and energy intensity, sometimes using the terms interchangeably. **Data granularity** was poor, as only a few studies used physical output data (e.g., Bruni et al., 2021, 2023; Wolniak et al., 2020), and while several applied firm-level data, most remained aggregated at 1- or 2-digit levels without addressing sectoral or process heterogeneity (Sahu et al., 2024; Solnørdal & Thyholdt, 2017; Yang et al., 2024). **Method-context alignment** was similarly weak, with only 6% tailoring their econometric models to reflect industrial diversity despite using advanced modeling techniques. These best-performing studies, based on detailed audit data from cement (Bruni et al., 2021) and plastics sectors (Costantini et al., 2024), demonstrate the value of high-resolution, context-specific data for meaningful energy efficiency evaluation in manufacturing.

Summary of methodological assessment

Assessment of 110 studies across six methodological approaches reveals significant variation in how well different methods address the fundamental challenges of manufacturing energy efficiency measurement. Table 1 summarizes the performance of each method type across the three key criteria—definition consistency, data granularity, and method-context alignment—and highlights studies that demonstrate good practice. While some methods perform better in particular criteria, most studies across all approaches fall short of good practices overall.

The results indicate that ratio-based methods perform best overall, demonstrating the strongest results in definition consistency (62%) and data granularity (50%). In contrast, more sophisticated approaches like econometric methods and frontier techniques often fall short of their potential, with econometric methods showing particularly weak data granularity (5–6%). Method–context alignment is the weakest area across all methods, with few studies tailoring their analytical approach to manufacturing heterogeneity. The strongest-performing studies consistently combine detailed, often physical data with explicit recognition of industrial heterogeneity—offering a path forward for more robust energy efficiency research in industry.

Discussions and conclusions

Our systematic review of 110 studies directly addresses the two key research questions posed in the introduction. First, regarding the methods used for country-level evaluation of EE in manufacturing and how they have evolved over time, we find that econometric approaches have become the most frequently applied in 2020–2024, while traditional approaches like IDA peaked in the earlier period (2010–2014) and ratio-based methods have declined yet remain foundational. This evolution reflects both the growing use of multi-stage analytical frameworks and the availability of more diverse and complex datasets. Second, with respect to how data choices and methodological design affect the reliability and validity of EE assessments, our evaluation across three criteria reveals that data granularity and method-context alignment remain critical weaknesses across most approaches. These shortcomings persist even in studies employing advanced techniques and substantially undermine result validity. Addressing these gaps is essential to improve the reliability and policy relevance of cross-country EE assessments in the manufacturing sector.

Building on these findings, we observe that despite the growing sophistication of methods used to assess industrial EE, the robustness and comparability of results are frequently compromised by recurring challenges. These challenges are not limited to specific techniques but reflect systemic risks that cut across methods. Based on our review, these risks can be organized into four interdependent levels: definition, data, method, and interpretation — with the latter often shaped by weaknesses in the first three. Figure 3 summarizes these risks and outlines targeted mitigation strategies.

At the definition level, inconsistencies in how EE is conceptualized remain a major issue. Ratio-based approaches, for instance, often equate energy intensity (energy/GDP) with EE, despite long-standing critiques that this metric captures structural or economic effects rather than technical improvements (Patterson, 1996; Phylipsen et al., 1997). In manufacturing, where energy intensity can vary dramatically between subsectors, a lack of clear technical definitions can undermine comparability and lead to misleading conclusions (Norman, 2017). Despite these limitations, we find that simple ratios are seldom applied in isolation; instead, they are typically integrated with complementary methods to strengthen the analysis. When used independently, they predominantly account for physical units of production, which enhances the validity of the results by providing a more direct measure of technical efficiency improvements.

The data level presents additional risks. Decomposition studies, particularly those using the Index Decomposition Analysis (IDA), are highly sensitive to the level of disaggregation. Analyses using 1- or 2-digit industry classifications may obscure key technological variations across subsectors (Hammond & Norman, 2012). Economic indicators used as output proxies introduce price-related distortions, while physical metrics are rarely available outside a few homogeneous, energy-intensive industries (Worrell

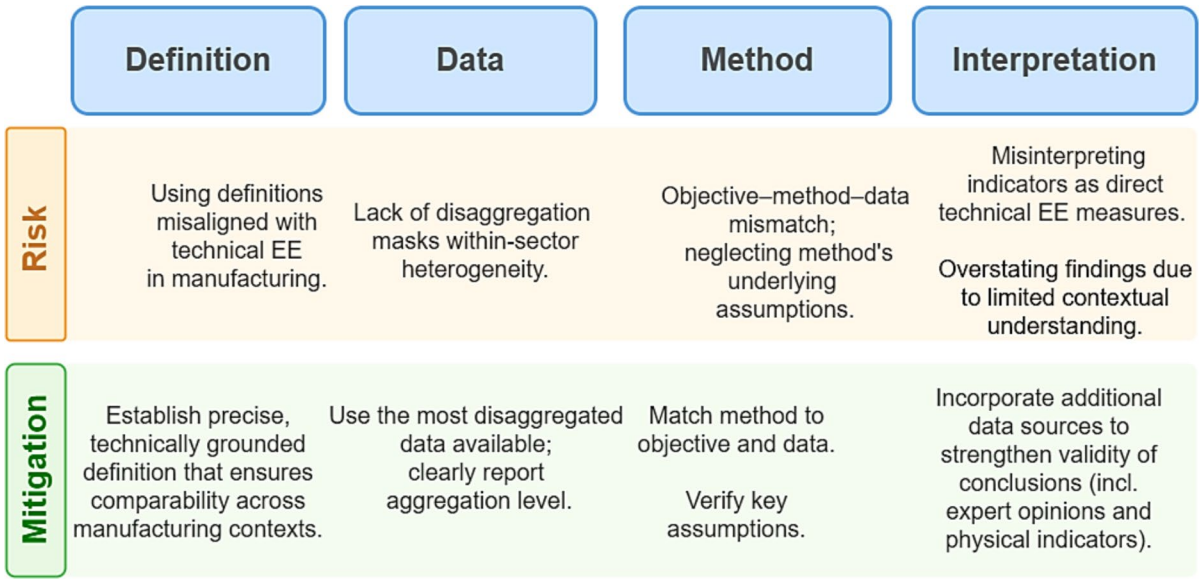

Fig. 3 Multi-level risks and mitigation in industrial energy efficiency assessment

et al., 2009). These data limitations constrain the granularity and robustness of results (Hoekstra & Van Der Bergh, 2003). However, our review also highlights that in some countries, additional statistical sources are available to supplement official statistical data. For instance, Denmark, Germany, China and the Netherlands studies incorporate data from industrial surveys, energy audits, or monitoring schemes to enhance sectoral coverage and detail. Yet, even firm-level surveys often provide only aggregated data at the 1- or 2-digit level and lack information on product mix or technologies used, limiting their ability to assess technical EE. In contrast, audit-based datasets, though typically covering a narrower sample, can offer higher-resolution information that strengthens the interpretation of sector-level trends.

At the methodological level, there can be some degree of misalignment between the assumptions underlying analytical methods and the realities of manufacturing systems. Frontier method such as DEA generally assume homogeneity among decision-making units (DMUs), an assumption difficult to justify given the heterogeneity in manufacturing technologies (Cook et al., 2013; Wu et al., 2019). DEA also attributes all deviations from the frontier to inefficiency, ignoring potential data noise, while SFA attempts to account for noise but requires strong distributional assumptions (Filippini & Hunt, 2015). Similarly, IDA's factor independence assumption rarely holds in practice, as activity, structure, and intensity effects often interact (Su & Ang, 2012), and changes caused by overlapping effects may be misattributed.

Finally, the interpretation of results introduces further risks. Indicators are sometimes used as direct measures of technical EE without acknowledging methodological or contextual limitations. Studies often lack supporting evidence from physical indicators, expert opinion, or process-level insights, which can lead to overstating efficiency gains or misattributing causality (IEA, 2014).

To address these risks, researchers are encouraged to ensure that methods align with data characteristics and research objectives (Wang et al., 2013). Prioritizing disaggregated, harmonized data can improve transparency and reduce aggregation bias (Phylipsen et al., 1997). In some contexts, combining methods—such as decomposition and frontier

analysis—may offer more robust insights (Camanho et al., 2024). Where available, physical indicators can better reflect technical efficiency, especially in homogeneous, energy-intensive sectors (Worrell et al., 2009). A practical example is the Odyssee-Mure project, which applies the ODEX index using physical indicators for energy-intensive branches (e.g. energy per ton of steel or cement) and complements quantitative results with country-level expert commentary to contextualize trends and reduce interpretation risks (Odyssee database, 2025; Country profiles, 2025; Lapillonne, 2020).

This study contributes to a more systematic understanding of the methodological risks in cross-country industrial EE assessment and highlights practical ways to improve the validity and comparability of results. The analysis focused on six widely used methodological approaches; other methods with lower prevalence in the literature were not examined in depth. Additionally, the review was limited to peer-reviewed publications indexed in the Scopus database, excluding other databases and grey literature. Future research could expand the scope to include a broader set of methods and sources, offering a more comprehensive view of current practices in both academic and policy contexts.

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Author Contribution J.A. conducted the literature review, performed the analysis, and wrote the manuscript. A.V. contributed to the conceptual development, supervised the work, and provided guidance on methodology and structure. All authors reviewed and approved the final manuscript.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

Appendix

Annex 1. Boolean search query for identifying relevant articles and inclusion and exclusion criteria

Boolean search query for identifying relevant articles

(TITLE-ABS-KEY("macro"OR"country*"OR"national"OR"international"OR"economy-wide"))
AND
(TITLE-ABS-KEY("manufactur*"OR"industr*"OR"production"OR"processing"OR"goods-producing"))
AND
(TITLE-ABS-KEY("energy efficien*"OR"energy intens*"OR"energy productiv*"))
AND
(TITLE-ABS-KEY("method*"OR"model*"OR"indicator*"OR"index*"OR"proxy*"OR"metric*"OR"assessment*"OR"quantification*"))
AND
(PUBYEAR > 2004 AND PUBYEAR < 2025)
AND
(DOCTYPE("ar") OR DOCTYPE("cp"))

Inclusion Criteria	Exclusion Criteria:
• Studies focused on country-level EE analysis in the manufacturing sector • Use of quantitative methods (e.g., IDA, SDA, DEA, SFA) for EE measurement • Empirical studies applying these methods to country-level or cross-national analysis • Articles published in English in peer-reviewed journals	• Articles not in English • Studies without a focus on manufacturing (e.g., broad industrial sector analyses) • Research that is too specific (e.g., plant, process- or technology-level assessments) • Studies focusing on CO_2 emissions rather than energy efficiency

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