A STANDARD-ALIGNED FRAMEWORK FOR ENERGY KPI CLASSIFICATION IN DISCRETE MANUFACTURING: A SYSTEMATIC REVIEW

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Parisa Zarenazhad

Examiners: Associate Professor Kalle Elfvengren

Post-doctoral researcher Mira Timperi-Koski

ABSTRACT

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Parisa Zarenazhad

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Keywords: Energy Key Performance Indicators; discrete manufacturing; energy performance; ISO 50001; KPI taxonomy; standard-aligned framework; systematic literature review

This thesis examines energy Key Performance Indicators (KPIs) in discrete manufacturing and develops a standard-aligned framework for classification and practical use. The main problem is inconsistent interpretation of energy-related indicators across studies. Similar KPI names can refer to different boundaries, calculation logic, and decision roles. This limits comparison and weakens the use of energy data as performance evidence. The study used a systematic literature review guided by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020. Scopus and Web of Science formed the main search path, and Google Scholar supported supplementary retrieval. The final review included 76 studies and 737 KPI entries. Each KPI entry was coded by energy status, KPI type, manufacturing level, measurement boundary, data type, calculation method, and standard relevance. International Organization for Standardization (ISO) 50001 was used as the main energy performance reference. ISO 22400 and ISO 20140 supported manufacturing operations and environmental manufacturing interpretation. The results show that direct energy KPIs dominate the reviewed literature. These indicators mainly measure energy consumption, power demand, efficiency, savings, and losses. Supporting KPIs explain output, machine state, downtime, and process context. Standard mapping showed that 78 percent of KPI entries aligned with ISO 50001, 15 percent with ISO 22400, and 29 percent with ISO 20140. The thesis contributes a KPI taxonomy with six groups and a decision framework. The framework starts from available operational data and checks level, boundary, data type, and required inputs before KPI type selection. The Hydroforming 8 application showed that power data, machine energy monitoring, and production output supported product level energy interpretation. The thesis gives a structured basis for moving from energy visibility to defensible energy performance evidence.

Symbols and abbreviations

Abbreviation	Full form
AI	Artificial Intelligence
CNC	Computer Numerical Control
CV	Coefficient of Variation
DBN	Deep Belief Network
EnPI	Energy Performance Indicator
GA	Genetic Algorithm
IoT	Internet of Things
ISO	International Organization for Standardization
KPI	Key Performance Indicator
LED	Light-Emitting Diode
MAPE	Mean Absolute Percentage Error
MES	Manufacturing Execution System
ML	Machine Learning
MLBM	Machine Load Balancing Method
MOM	Manufacturing Operations Management
OEE	Overall Equipment Effectiveness
PAEE	Part Energy Efficiency
PLC	Programmable Logic Controller
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RFID	Radio Frequency Identification
RQ	Research Question
SCADA	Supervisory Control and Data Acquisition
SEC	Specific Energy Consumption
VB	Flank tool wear value

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DECLARATIONS

Turnitin

The originality of this thesis has been reviewed with the Turnitin similarity checking service.

AI usage

The author of this thesis, Parisa Zarenazhad, used the following AI-tools during the preparation of the thesis:

1. AI tool Grammarly
    a. Purpose of use: supporting grammatical accuracy, sentence clarity.
    b. Explanation of the use of the tool: Grammarly was used to support language editing of the thesis text. The tool helped identify grammar issues, spelling mistakes, punctuation problems, and unclear sentence structures. Its suggestions were reviewed by the author before acceptance, and the tool was not used to generate research content, analysis, results, or interpretations.
2. AI tool ChatGPT
    a. Purpose of use: supporting language refinement, sentence restructuring, wording improvement, and clarity improvement in draft sections of the thesis.
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Responsibility

The author, Parisa Zarenazhad, takes full responsibility for the content of this thesis and has reviewed and edited the content generated by the possible use of AI tools.

1 Introduction

This chapter introduces the conceptual background of the study by showing that energy performance in manufacturing cannot be interpreted through raw consumption data alone and that indicator interpretation is especially important in discrete manufacturing. It then defines the research gap concerning the comparison, classification, and application of energy-related indicators. To address this gap, the thesis uses a systematic literature review guided by the PRISMA approach to identify, screen, and analyze studies on energy Key Performance Indicators (KPIs) in discrete manufacturing. The extracted KPI evidence is then organized into a taxonomy and interpreted through a standard-aligned framework.

1.1 Background and Motivation

Improving energy efficiency in manufacturing is a strategic and organizational challenge that affects cost control, competitiveness, and production performance. Recent tertiary review evidence presents manufacturing energy efficiency as a field that combines process, technical, and leadership knowledge (Ibn Batouta et al. 2023). Effective implementation depends on structured energy management, leadership commitment, and coordination across functions (Miera et al. 2026). Integrating energy efficiency into production decision making remains difficult in practice. This difficulty supports treating energy performance as part of the production system beyond isolated energy accounting (Wen et al. 2021).

This issue is especially important in discrete manufacturing. Discrete manufacturing refers to production systems where individual parts are produced in separate operations involving machines, process steps and connected production lines. Energy use in this context is shaped by machine states, product variation, process conditions and interactions across operational manufacturing levels (Diaz & Ocampo-Martinez 2019). At the machine level, especially in machining operations, energy use is distributed across material removal, start-up, standby, air-cutting, idle states, and auxiliary functions (Sihag & Sangwan 2020). This makes discrete manufacturing a relevant context for studying energy KPIs because similar energy indicators may have different meanings depending on operating state, boundary, and production level.

For this reason, performance measurement is essential in energy management. In manufacturing, raw consumption data alone do not show efficiency, comparability or operational meaning. These data need to be translated into indicators for monitoring, comparison and improvement. Meaningful energy indicators depend on measured values, relevant variables, system boundaries and assessment level (Benedetti et al. 2017; Kanchiralla et al. 2020).

1.2 Research Gap and Problem Statement

Recent tertiary review evidence shows that manufacturing energy efficiency research is distributed across diagnostic, metering, optimization, technology, strategic, and driver and barrier streams. Existing studies provide useful evidence on manufacturing energy performance. However, the field still lacks a consistent basis for comparing indicator meaning, calculation logic and use across studies (Ibn Batouta et al. 2023). This issue becomes more visible in discrete manufacturing. Energy consumption is influenced by machine states, process conditions and production configurations. In this context, energy indicators are often developed for specific machines, processes or decision problems. Research on machine tools and machining processes shows that energy-related work has expanded, but common assessment logic and standardized indicator use remain limited (Diaz & Ocampo-Martinez 2019; Sihag & Sangwan 2020).

A further issue is that studies use different indicator boundaries, manufacturing levels and measurement logics. Some indicators describe total or state-based energy consumption. Other indicators represent specific, intensity-based, operational or benchmarking purposes. Indicator-oriented work shows that energy KPI interpretation requires clear energy end-use categories, system boundaries and assessment purposes (Kanchiralla et al. 2020). Figure 1 summarizes the main sources of inconsistency in energy KPI interpretation.

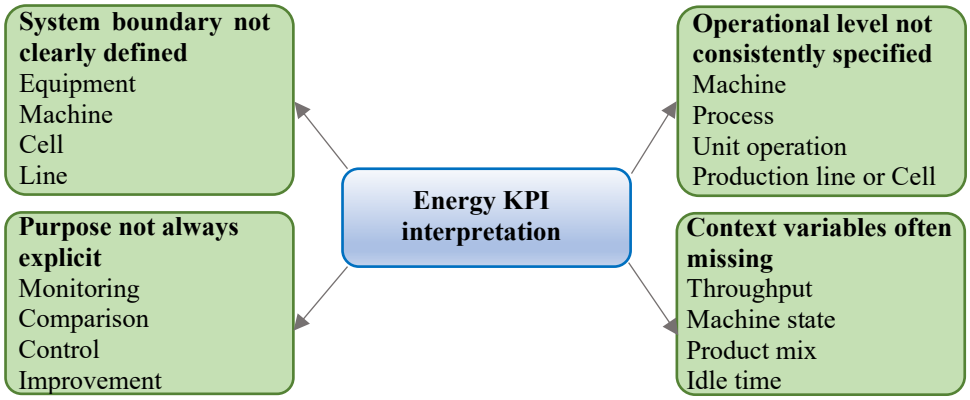

Figure 1. Contextual sources of inconsistency in energy KPI interpretation. Synthesized from Benedetti et al. (2017), Diaz and Ocampo-Martinez (2019), and Kanchiralla et al. (2020).

Figure 1 shows that KPI interpretation depends on operational level, system boundary, context variables and interpretation purpose. These factors can make similar KPI names represent different meanings across studies. This creates difficulty in comparing, classifying and mapping energy-related indicators in a consistent way.

This matter causes the main research gap of this thesis. The gap concerns the lack of a clear and systematic understanding of energy-related indicators in discrete manufacturing, especially their meaning, role and comparability across studies. The types of energy KPIs, their intended purposes, their levels of application and their links to operational indicators and industrial standards remain insufficiently clarified. As a result, comparing studies and interpreting energy performance evidence across manufacturing contexts remains difficult.

1.3 Research Objectives and Research Questions

The purpose of this thesis is to systematically review energy KPIs in discrete manufacturing and develop a standard-aligned framework for their classification, interpretation and practical use. The framework is based on evidence extracted from the reviewed literature and is demonstrated with one real industrial operational dataset. The specific objectives are:

- to identify energy KPIs reported in the literature on discrete manufacturing.
- to examine the definitions and calculation methods of these KPIs across different manufacturing contexts.
- to classify the identified KPIs into an operational KPI taxonomy for discrete manufacturing.

- to assess their alignment with International Organization for Standardization (ISO) 50001 as the primary energy-performance standard, and with ISO 22400 and ISO 20140 as complementary contextual standards under predefined mapping rules.
- to demonstrate the practical feasibility of the framework through an illustrative application using one real industrial operational dataset

Based on these objectives, the thesis addresses the following research questions:

RQ1. What energy KPIs are reported in discrete manufacturing operations, and how are they defined and computed?

RQ2. What taxonomy can be used to structure the identified energy KPIs for discrete manufacturing operations?

RQ3. Which identified energy KPIs can be mapped to ISO 50001:2018 as the primary standard, and which can be interpreted in relation to ISO 22400 and ISO 20140 under predefined secondary mapping rules?

RQ4. Using one real industrial operational dataset, which energy KPIs are practically extractable with minimal assumptions, and what example outputs can illustrate the feasibility of the proposed framework?

1.4 Scope of the Study

This thesis focuses on energy KPIs reported in the context of discrete manufacturing systems. The review is limited to studies that address manufacturing operations at machine, process, unit operation, or production-line level and report at least one defined, computable, or clearly operationalizable energy KPI based on measured, recorded, or operationally grounded manufacturing data.

The study is limited to energy-related KPIs and does not aim to develop a general library of all manufacturing performance indicators. Operational indicators that are not directly energy-related are considered only when they support the interpretation of energy performance. In addition, the review excludes studies that focus exclusively on continuous or process industries, building or campus energy management unrelated to production, purely conceptual discussions without measurable indicators, and studies that do not provide sufficient information to identify and interpret the KPI.

With regard to standards, the study uses ISO 50001:2018 as the primary reference standard for direct energy-related KPIs. ISO 22400 and ISO 20140 are considered only in a complementary contextual role under predefined mapping rules. Finally, the empirical part of the thesis is limited to an illustrative feasibility demonstration using one real industrial operational dataset, rather than a large-scale empirical testing across multiple industrial cases.

1.5 Structure of the Thesis

This thesis has eight chapters. Chapter 1 introduces the background of the study. It also presents the research gap, objectives, research questions, scope and thesis structure. Chapter 2 explains the main concepts used in the study. It covers energy management, energy KPIs, energy performance indicators (EnPIs), and the selected reference standards. Chapter 3 describes the research method. It presents the systematic review, search strategy, screening process, data extraction, KPI classification, and standard mapping. Chapter 4 presents the results of the systematic review. It shows the distribution of the extracted KPIs across the main analytical dimensions used in the thesis. Chapter 5 develops the KPI taxonomy from the extracted evidence. Chapter 6 presents the proposed framework for structuring and interpreting energy KPIs. It also applies the framework to the illustrative dataset. Chapter 7 discusses the main findings and their implications for energy management and KPI design. Chapter 8 concludes the thesis by summarizing the findings contributions, limitations, and future research directions.

2 Background and Conceptual Foundations

This chapter provides the conceptual foundation for interpreting energy performance in discrete manufacturing. It covers energy management, energy efficiency, selected standards, KPIs, EnPIs and operational indicators. It also discusses key challenges in defining, interpreting and comparing energy-related KPIs across manufacturing contexts.

2.1 Energy Management and Energy Efficiency in Manufacturing

Energy efficiency in manufacturing should be understood as a production and management issue. Energy performance is shaped by production system structure, manufacturing context and operational conditions (Renna & Materi 2021). This point becomes important across hierarchical levels because equipment states and production changes affect energy performance interpretation (Cao et al. 2021).

At the operational level, effective energy management needs digital and analytical support that makes energy use visible, interpretable and useful for decisions. This support covers energy monitoring, performance evaluation and identification of production inefficiencies. Performance measurement gives indicators a defined role when their purpose, application level and calculation logic are clear, helping firms select indicators and connect them to concepts and decision levels (Cagno et al. 2023). Industry 4.0 technologies can strengthen energy management by supporting energy monitoring, performance evaluation and energy efficient process design in manufacturing (Benedetti et al. 2017; Cagno et al. 2025).

A further issue is the separation between energy efficiency and production management. This separation limits the identification of energy saving opportunities embedded in operations. Integrating energy efficiency into production management can improve manufacturing system performance while maintaining productivity. This integration remains difficult because the relationship between energy efficiency and productivity is still not sufficiently understood (Cagno et al. 2025; Wen et al. 2021).

In discrete manufacturing, energy consumption is embedded in the way parts are produced, moved and scheduled. In machining operations, non-cutting states can account for 20-40%

of total energy consumption in a complete machining process. These states include standby, spindle acceleration, spindle idling, rapid feed and feed movement (Luan et al. 2019, 4451).

Computer Numerical Control (CNC) machine tool studies support the same point because energy demand is shaped by material removal and by non-cutting activities such as standby, auxiliary functions, spindle rotation and feeding (Lv et al. 2016). At job shop and production line level, the same production requirement can lead to different energy outcomes because alternative machines, operation sequences and idle periods change machining energy and waiting energy (He et al. 2015). For this reason, energy KPIs in this thesis are treated as indicators that depend on context. Their interpretation requires a defined measurement boundary, manufacturing level and calculation logic. This point links energy management in discrete manufacturing with the classification dimensions used in this thesis.

2.2 Reference Standards for Energy and Manufacturing KPIs: ISO 50001, ISO 22400, and ISO 20140

In this thesis, ISO standards function as conceptual reference points for interpreting manufacturing KPIs. They are not used as detailed compliance checklists. Their role is to clarify the measurement purpose of different indicator types and their contribution to monitoring and improvement. ISO 50001 is the main reference standard because it focuses on energy performance and EnPIs. ISO 22400 and ISO 20140 are used as complementary standards. ISO 22400 supports operational manufacturing KPI interpretation, and ISO 20140 supports environmental manufacturing performance interpretation (ISO 20140-1 2019; ISO 22400-1 2014; ISO 50001 2018). Table 1 clarifies the different purposes of the selected standards and their roles in this thesis.

Table 1. Roles of the selected reference standards in this thesis.

Standard	Main purpose of the standard	Key concepts used in this thesis	Role in this thesis
ISO 50001	Supports energy management and energy performance improvement.	Energy performance, EnPI, energy baseline.	Primary reference for direct energy performance indicators and ISO 50001 mapping.
ISO 22400	Defines KPIs for manufacturing operations and decision support.	KPI scope, formula, unit, timing.	Complementary reference for operational KPI structure and manufacturing context.
ISO 20140	Supports environmental performance evaluation of manufacturing systems.	Environmental performance, environmental KPI, benchmarking.	Complementary reference for environmental manufacturing performance interpretation.

Table 1 shows that ISO 50001 gives the main energy performance basis. ISO 22400 gives the operational KPI structure. ISO 20140 gives the environmental manufacturing perspective. These roles guide the mapping logic used later in the thesis.

ISO 50001:2018 is the primary standard in this thesis because it defines the logic of energy performance management. The standard links energy performance with energy use, energy efficiency and energy consumption. It defines an EnPI as a measure or unit of energy performance determined by the organization. EnPIs may be defined as a model, ratio or single metric depending on the measured activity. ISO 50001 requires suitable EnPIs for monitoring energy performance and demonstrating improvement. For this reason, ISO 50001 provides the main reference for direct energy-related KPIs in discrete manufacturing (ISO 50001 2018).

ISO 22400 has a complementary role in this thesis. It defines KPIs for Manufacturing Operations Management (MOM), which covers production activities between enterprise planning and shop floor control. ISO 22400 is relevant because it defines KPI structure and the contextual information needed for operational interpretation. Part 1 states that KPIs support operational performance improvement and decision support. It specifies that a KPI should include scope, formula, unit of measure, timing, usage and applicable production methodology (ISO 22400-1 2014). Part 2 provides definitions of specific KPIs used in manufacturing operations management (ISO 22400-2 2014). Overall Equipment Effectiveness (OEE) is used in this thesis as an example of an operational KPI because it combines availability, performance and quality. This distinction helps separate operational KPIs from direct energy KPIs.

ISO 20140 provides the environmental manufacturing perspective. It supports the evaluation of environmental performance in manufacturing systems, including energy consumption, waste and release. The standard applies to discrete, continuous and batch manufacturing and supports benchmarking, improvement targets and visualization of environmental performance. Part 1 provides the general principles, and Part 2 defines the environmental performance evaluation process (ISO 20140-1 2019; ISO 20140-2 2018). In this thesis, ISO 20140 has a complementary role because its focus is environmental manufacturing performance, while ISO 50001 provides the primary basis for direct operational energy performance at KPI level.

2.3 Energy KPIs, EnPIs, and Energy Performance Measurement Logic

Performance measurement links operational data with management action. Raw energy data show measured values. These values gain performance meaning after the indicator objective, scope, formula, unit, timing and use context are defined. These elements support interpretation, comparison and decision use in manufacturing operations (ISO 22400-1 2014). In this thesis, this logic gives the foundation for KPI extraction and classification. Reported energy values become usable evidence after their boundary, data basis, calculation logic and intended use are clear. Standard KPI definitions require contextual checking because production settings, measurement elements affect relevance and computability (Zhu et al. 2018). At implementation level, KPI monitoring depends on runtime data, computable variables, event records and formula execution (Ramis Ferrer et al. 2018). EnPIs provide the formal energy performance concept for indicators that directly measure energy performance (ISO 50001 2018). Table 2 summarizes the conceptual relationship between indicator terms and their role in this thesis.

Table 2. Key indicator concepts used in this thesis.

Concept	Meaning in this thesis	Performance measurement role	Use in this thesis
Raw energy data	Measured energy or power values from manufacturing operations	Gives the measured basis before KPI interpretation	Used as the input basis for energy KPI extraction and dataset application
KPI	A quantifiable indicator linked to a performance objective	Connects measured data with scope, formula, unit, timing and use context	Provides the general structure for interpreting manufacturing indicators
Energy performance	Measurable result related to energy efficiency, energy use and energy consumption	Defines the performance domain assessed by the thesis	Defines the scope of direct energy KPI interpretation
EnPI	A measure or unit of energy performance defined by an organization	Gives the formal energy management indicator logic	Provides the main basis for ISO 50001 mapping
Direct energy KPI or EnPI	Indicator that directly measures energy performance	Turns energy data into direct performance evidence	Used for KPI classification and ISO 50001 mapping
Supporting KPI	Indicator that explains the operating context behind energy performance	Supports interpretation of direct energy KPI values	Used for boundary, state, output and process context interpretation
Framework role	Analytical function of a KPI in the thesis framework	Separates measurement evidence, decision evidence and supporting evidence	Used to classify KPIs as measurement enabling or decision-layer or supporting

Table 2 links the main indicator concepts with the measurement logic used in this thesis. Direct energy KPIs or EnPIs measure energy performance. Supporting KPIs explain the operating context behind energy performance values. These categories guide KPI extraction, standard mapping, taxonomy development, and framework role assignment. Electricity demand, fuel consumption, operating hours, and production output gain value after boundary, relevant variables, and assessment level are defined (Kanchiralla et al. 2020). Supporting KPIs are retained because operating context, production output, and machine state affect the interpretation of direct energy KPIs and EnPIs (Benedetti et al. 2017).

2.4 Challenges in Defining and Interpreting Energy KPIs in Discrete Manufacturing

Defining and interpreting energy KPIs in discrete manufacturing is difficult because energy performance is shaped by technical, operational and managerial factors across machine, process, unit operation and line or cell levels. KPI definitions depend on system boundary, aggregation level, data basis and intended decision use. This condition makes consistent interpretation difficult across studies and applications (Benedetti et al. 2017; Kanchiralla et al. 2020).

A first challenge concerns heterogeneous manufacturing levels and system boundaries. A KPI that is meaningful at machine level may have a different meaning at process or line level. Similar KPI names may therefore refer to different scopes, boundaries and decision contexts (Benedetti et al. 2017; Diaz & Ocampo-Martinez 2019).

A second challenge concerns inconsistent KPI definitions and calculation logic. Energy KPIs may be reported as absolute measures, ratios, specific energy consumption indicators, indicators derived from models or indicators used for benchmarking. These forms rely on different variables, formulas and normalization principles, and they serve different analytical purposes. Comparison therefore needs clear boundary definition and contextual interpretation (Benedetti et al. 2017; Kanchiralla et al. 2020).

A third challenge concerns operational information. Variables such as throughput, downtime, product mix, changeovers and machine states shape the interpretation of direct energy KPI values. This issue is especially relevant in discrete manufacturing because machine behavior, operating modes and production flows shape energy use across machine,

process and line contexts (Diaz & Ocampo-Martinez 2019). This thesis treats such variables as supporting indicators when they clarify energy performance conditions.

Methodological diversity adds another difficulty. A recent tertiary review shows that manufacturing energy efficiency is studied across connected areas, including measurement, diagnosis, optimization, and technology use (Ibn Batouta et al. 2023). This diversity makes KPI comparison harder and supports structured extraction, classification, and standard-aligned interpretation. Figure 2 summarizes the main challenges in defining and interpreting energy KPIs in discrete manufacturing.

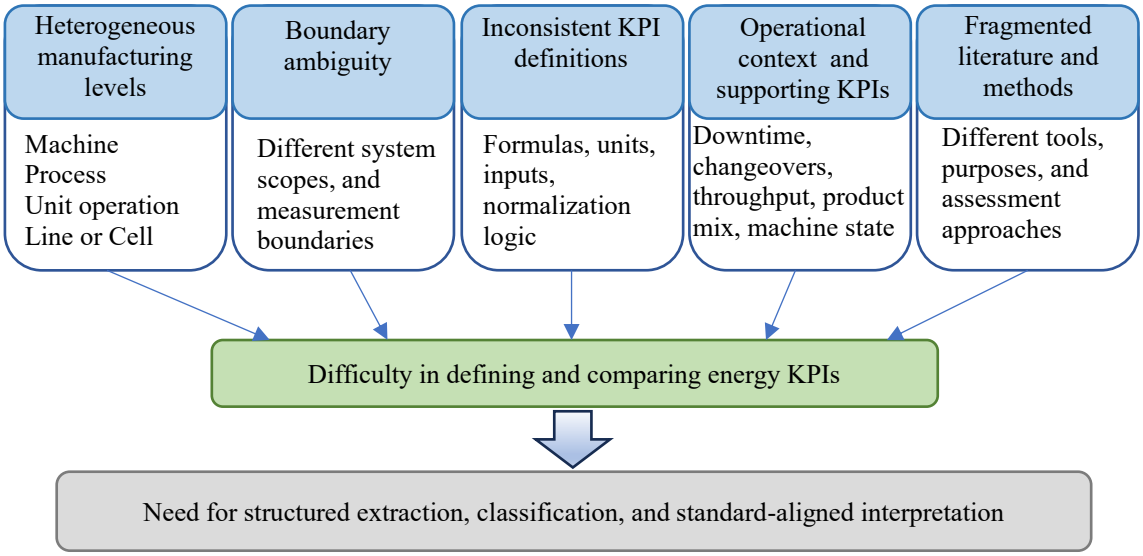

Figure 2. Main challenges in defining energy KPIs in discrete manufacturing.

Figure 2 shows that KPI interpretation depends on manufacturing level, boundary, definition logic, operational context and methodological basis. These factors can make similar KPI names represent different meanings across studies. This creates difficulty in defining, comparing and mapping energy-related indicators in a consistent way.

These challenges show that energy KPI analysis needs consistent definitions, clear boundaries, contextual interpretation, and structured classification. In discrete manufacturing this requires attention to hierarchical level and operational conditions and intended decision use and supports the methodological approach in the next chapter.

3 Research Methodology

This chapter explains the systematic literature review method and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 documentation used in this thesis. It presents the research design, search strategy, eligibility criteria, screening process, data extraction procedure, KPI classification and standard mapping. The Scopus and Web of Science search strings and the supplementary Google Scholar search strings are provided in the appendices (Appendices 1-2). The detailed study selection counts underlying the PRISMA 2020 flow diagram and the final selected studies with paper IDs, titles, publication years and citation keys are also reported in the appendices (Appendices 3- 4).

3.1 Research Design

This thesis adopts a systematic literature review as its main research design. This approach was selected because the study aims to identify, structure and interpret dispersed evidence on energy KPIs reported in discrete manufacturing. The empirical dataset is used later as an illustrative framework application. A systematic review is suitable for this purpose because the evidence is fragmented and requires a transparent and reproducible synthesis. It provides a structured basis for analyzing energy KPIs across manufacturing contexts and operational levels (Tranfield et al. 2003). Systematic reviews differ from conventional narrative reviews because they use explicit procedures for searching, selecting and documenting studies. This reduces arbitrary selection and creates an auditable process. In this thesis, this logic is important because the objective is to locate relevant studies and support the later extraction, classification and interpretation of energy KPIs in a consistent and defensible manner (Tranfield et al. 2003).

The review was guided by a predefined protocol before the main screening stages. The protocol defined the review scope, research questions, search boundaries, screening logic and extraction structure. This supported consistency, transparency and defensible handling of records during study selection and data extraction (Moher et al. 2015).

This review was designed to identify reported energy KPIs and support their classification and standard-aligned interpretation. This design follows manufacturing oriented assessment

logic, where indicator selection, goal definition and boundary specification support meaningful assessment and communication (Kanchiralla et al. 2020; Paju et al. 2010). PRISMA 2020 was used to document record identification, screening, eligibility assessment and inclusion (Page et al. 2021).

3.2 Systematic Literature Review and PRISMA Approach

This review used a systematic literature review method to identify, screen and interpret research on energy KPIs and EnPIs in discrete manufacturing. Study identification, selection and documentation followed predefined procedures instead of ad hoc literature collection. This supported a transparent and defensible review process (Tranfield et al. 2003). The review followed a protocol that specified the review objective, research questions, database coverage, publication year range, document types, title and abstract screening rules, full text screening rules, exclusion codes, extraction logic and principles for KPI classification and standard mapping. This protocol supported consistent handling of borderline cases during screening and extraction (Moher et al. 2015).

PRISMA 2020 is a reporting guideline for systematic reviews. It supports transparent reporting of study identification, screening, eligibility assessment and inclusion. Its checklist covers information sources, eligibility criteria, search strategy, selection process and study selection results. It is supported by flow diagrams that show the movement of records from identification to final inclusion (Page et al. 2021). In this thesis, PRISMA 2020 was used to document the literature search and study selection process. The KPI level analytical work was conducted separately after study inclusion. This means that KPI extraction, KPI classification and standard mapping were based on the thesis protocol and coding rules, while PRISMA 2020 was used to report the review process clearly.

The review combined primary database searches in Scopus and Web of Science with supplementary Google Scholar searches. Scopus and Web of Science formed the structured primary search path. Google Scholar was used as a supplementary path to identify additional relevant studies. The primary database path identified 324 records. After duplicate removal, 214 records remained for title and abstract screening. The Google Scholar path identified 157 records. After duplicate removal, 96 records remained for title screening. Across the primary and supplementary paths, 76 studies were included in the final review.

Screening was staged. Title and abstract screening used broad inclusion logic. Full text screening applied stricter eligibility and extractability criteria from the protocol. The detailed study selection counts, search waves, Run IDs, report retrieval status and full text exclusion reasons are reported separately (Appendix 3). Figure 3 presents the PRISMA 2020 flow diagram for record identification, screening, eligibility assessment and final inclusion.

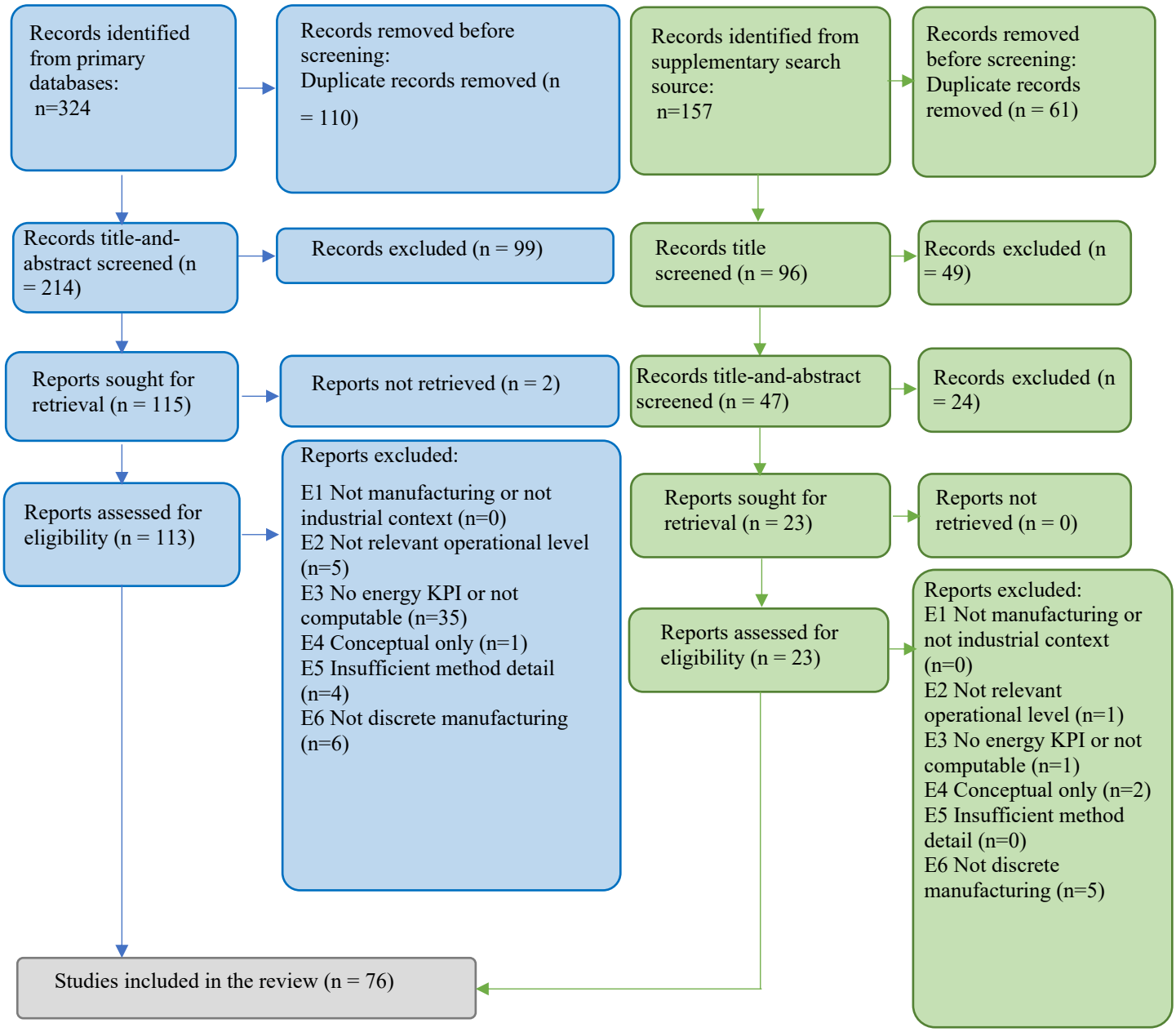

Figure 3. PRISMA 2020 flow diagram summarizing the study selection process used in this review. Scopus and Web of Science served as the primary databases, and Google Scholar was used as a supplementary search source.

Figure 3 shows the movement of records from identification to final inclusion. It separates primary database records from supplementary Google Scholar records and shows the main screening decisions. This documentation supports transparency and traceability in the selection of the 76 studies included in the review (Page et al. 2021). The following sections explain the database searches, eligibility criteria, screening logic and extraction procedures.

3.3 Databases and Search Queries

The database search strategy was designed to identify studies reporting energy-related KPIs or EnPIs in discrete manufacturing operations at machine, process, and line or cell level. The review aimed to identify studies with indicators suitable for mapping within discrete manufacturing and to avoid an overly general energy management scope. Therefore, the search strategy had to balance broad coverage with operational relevance. In addition, PRISMA 2020 requires clear documentation of information sources, search strategies, filters and limits (Page et al. 2021).

Scopus and Web of Science were selected as the primary databases for the structured search. This choice was appropriate for the present thesis because both databases support controlled, filterable, and well-documented searching across engineering and applied industrial literature. Google Scholar was used as a supplementary source to improve the completeness of study identification by capturing additional relevant studies not fully retrieved through the primary databases. PRISMA 2020 requires reporting all searched information sources and the last search date for each source (Page et al. 2021).

The search strings were constructed around several concept blocks derived from the review scope and research questions. The first block captured the indicator concept through terms such as energy KPI, energy performance indicator, EnPI, energy metric, and energy indicator. This was necessary because the literature does not use a single stable term for operational energy indicators. A second block captured the industrial context through terms such as manufactur*, industrial, production, factory, machine tool, machining, and production equipment. A third block was introduced in the refinement searches to target operational level more explicitly, distinguishing between machine-level, process-level, and line- or cell-level contexts. A fourth block focused on data and implementation cues,

including programmable logic controller (PLC), supervisory control and data acquisition (SCADA), manufacturing execution system (MES), time series, real-time, sensor data, process data, operational data and measured data. These terms were included because they refer to industrial control, monitoring and execution systems used to record and manage manufacturing process data. This data-oriented block helped retrieve studies in which energy KPIs were linked to measured, recorded or operational manufacturing data. It also helped exclude purely conceptual indicator discussions from the search focus.

The search was implemented in multiple waves to capture the broad vocabulary and the operational levels relevant to the review. Initial searches in Scopus and Web of Science were intentionally broad to capture the wider vocabulary used around energy KPIs and EnPIs in industrial manufacturing. However, the broad searches alone were not sufficient for the review objective, because they did not guarantee adequate retrieval of studies at the specific operational levels relevant to the thesis. For this reason, refinement searches were conducted to improve capture of machine-level or equipment-level studies, process-level or unit-operation studies, and line-level, cell-level, or production-system studies. This staged design reflects the review logic because the focus was energy KPI evidence situated at operational manufacturing level.

The applied filters reflected the methodological scope of the review. The year range was limited to 2015-2026 to focus the review on recent digitalized manufacturing contexts, including sensor-based monitoring, IoT-enabled data collection, digital twins and data-driven KPI computation. Only journal and conference or proceeding papers were considered, while books and patents were excluded. This was appropriate because the review required sufficiently structured methodological reporting to support screening, extraction, and later KPI classification. English-language filtering was applied in the primary databases for consistency of screening and interpretation. For Google Scholar, however, language and document-type filters were not directly available, so these constraints were handled later during title or abstract screening according to the predefined review protocol. Table 3 summarizes the main database searches conducted in this review, including the broad primary searches, the refinement searches by operational level, and the supplementary Google Scholar searches.

Table 3. Summary of the search strategy.

Run ID	Database	Search focus	Filters applied	Results returned	Role in search strategy
S01	Scopus	Broad primary search	Publication years 2015-2026; journal articles and conference papers; English language	524	Preliminary scoping search used to assess literature volume and refine later search terms. Not included in PRISMA screening counts.
S01a	Scopus	Machine-level refinement	Publication years 2015-2026; journal articles and conference papers; English language	23	Improved retrieval of studies focused on machine-level or equipment-level energy KPIs and EnPIs
S02	Web of Science	Broad primary	Publication years 2015-2026; journal articles and proceedings papers; English language	134	Preliminary scoping search used to assess literature volume and refine later search terms. Not included in PRISMA screening counts.
S02a	Web of Science	Machine-level refinement	Publication years 2015-2026; journal articles and proceedings papers; English language	94	Improved retrieval of studies focused on machine-level or equipment-level energy KPIs and EnPIs
S01b	Scopus	Process-level refinement	Publication years 2015-2026; journal articles and conference papers; English language	27	Targeted retrieval of studies focused on process-level or unit-operation-level energy KPIs and EnPIs
S01c	Scopus	Line-level and cell-level refinement	Publication years 2015-2026; journal articles and conference papers; English language	1	Targeted retrieval of studies focused on line-level, cell-level, or production-system-level energy KPIs and EnPIs
S02b	Web of Science	Process-level refinement	Publication years 2015-2026; journal articles and proceedings papers; English language	97	Targeted retrieval of studies focused on process-level or unit-operation-level energy KPIs and EnPIs
S02c	Web of Science	Line-level and cell-level refinement	Publication years 2015-2026; journal articles and proceedings papers; English language	82	Targeted retrieval of studies focused on line-level, cell-level, or production-system-level energy KPIs and EnPIs
S03a	Google Scholar	Supplementary machine-level	Publication years 2015-2026	78	Supplementary retrieval of additional machine-level studies not fully captured in the primary database searches
S03b	Google Scholar	Supplementary process-level	Publication years 2015-2026	64	Supplementary retrieval of additional process-level studies not fully captured in the primary database searches
S03c	Google Scholar	Supplementary line-level and cell-level	Publication years 2015-2026	15	Supplementary retrieval of additional line-level or cell-level studies not fully captured in the primary database searches

Note: Broad primary searches were used as preliminary scoping searches. They are reported for transparency but were not included in the PRISMA screening counts.

Finally, each search was recorded in a search log which included run ID, source database, search date, exact query, filters applied, number of records retrieved, export format, and search notes. This search log created an audit trail for the search phase. Complete search strings are provided in the appendices (Appendices 1-2). The next section describes the screening and eligibility assessment of the collected records.

3.4 Inclusion and Exclusion Criteria

The study selection process involved two sequential phases. The first phase was title-and-abstract screening, and the second phase was full-text screening. These phases used different levels of evidence. Title-and-abstract screening removed only clearly irrelevant records and retained uncertain studies for later assessment. Full-text screening then applied the complete eligibility criteria. The final inclusion decision was based on the definition, operationalization and extractability of the reported KPIs or EnPIs.

Records retrieved from Google Scholar first underwent preliminary title screening before title-and-abstract screening. This step was needed because Google Scholar records did not consistently include abstracts in the exported dataset. Title screening removed clearly ineligible records before the retained records moved to title-and-abstract assessment.

Criteria for Title-and-Abstract Screening

At the title-and-abstract stage, a record was classified as Include only when the title-and-abstract clearly indicated all three of the following conditions:

1. a discrete industrial manufacturing context.
2. an explicit energy focus, such as energy consumption, energy efficiency, energy management, or an energy KPI or EnPI.
3. an energy-related method, application, or use, for example monitoring, analytics, modelling, optimization, IoT-based systems, digital twins, machine learning, or a clear indication that the study used operationally grounded manufacturing data.

A record was classified as Exclude when the title-and-abstract clearly showed that it was not related to manufacturing, not related to discrete manufacturing, had no energy focus, or was otherwise clearly outside the review scope. To reduce the risk of excluding relevant studies

too early, an Uncertain category was used. A record was coded as Uncertain when the title and abstract suggested possible relevance but did not provide enough evidence for a clear Include decision. These records were retained for full-text screening, where the stricter eligibility criteria were applied.

Additional Title Screening for Google Scholar

Preliminary title screening was applied only to Google Scholar records. Scopus and Web of Science records moved directly to title-and-abstract screening because, unlike Google Scholar, their exported records included abstracts. At this stage, records were removed only when the title made it immediately clear that they belonged to one of the following categories:

E1: not manufacturing or not industrial context

E7: not written in English

E10: not a journal article, conference paper, or proceedings paper

This step was deliberately conservative. It removed only records that were clearly ineligible before abstract-based screening. Codes E7 and E10 were used only in the Google Scholar stream because Google Scholar did not provide the same pre-filtering control for language and document type as the primary databases.

Criteria for Full-Text Screening

Full-text screening applied the eligibility criteria defined in the review protocol. A paper was counted as included only if it met all of the criteria listed below.

First, the paper had to address discrete manufacturing operations at the relevant manufacturing level, including machine, process or unit operation, or production line and cell. Papers outside these operational levels were excluded because the review focuses on operation-level energy KPIs.

Second, the study had to report at least one energy KPI, EnPI, or energy-related metric with enough detail for extraction or mapping. In this review, an energy KPI or EnPI was retained as an extracted KPI entry when the study provided enough information to document its name or description, unit, operational boundary, required inputs, and explicit formula or clearly inferable calculation logic. A KPI or EnPI was considered mapping-ready when its

description supported consistent taxonomy classification and alignment with ISO 50001:2018, and, where applicable, ISO 22400 or ISO 20140.

Third, the study had to use measured, recorded or operationally grounded manufacturing data, such as sensors, smart meters, SCADA, PLC, MES, IoT logs, audit datasets, baseline datasets, or derived and model-based indicators linked to real manufacturing operations and defined input variables. This requirement separated operationally meaningful indicators from theoretical or abstract formulations.

Fourth, the study had to provide enough methodological information to extract the KPI definition, input requirements and calculation approach. A study could be retained without an explicit closed-form formula when the calculation logic was clear enough for defensible inference. Raw signals, such as voltage traces or current measurements, were treated as KPIs only when the study described their transformation into an energy KPI or EnPI. Studies that failed one or more essential conditions were excluded at full-text screening and assigned one primary exclusion code.

Logic and Use of Exclusion Codes

To ensure consistency and transparency, all exclusion decisions were recorded using predefined exclusion codes (E1-E10). The coding scheme was designed to follow a sequential logic, especially for E1-E6, so that the most fundamental and most informative reason for exclusion was recorded first.

The sequence was applied as follows:

E1: not manufacturing or not industrial context

E2: not relevant operational level (not manufacturing machine/process/line)

E3: no energy KPI or not computable

E4: conceptual only (no definition or inputs)

E5: insufficient method detail

E6: manufacturing but not discrete manufacturing (process or continuous manufacturing), applied only when E1-E5 could not be applied

This ordering was intentional. E1 was used for studies outside manufacturing. E2 was used when the study addressed manufacturing but lacked the relevant operational level. E3 was

used when the context and level were relevant but no defined or computable energy KPI was reported. E4 was used for conceptual energy-improvement discussions without measurable inputs or a definable indicator. E5 was used for studies that appeared relevant but lacked enough methodological detail for extraction. E6 was reserved for energy-related manufacturing studies from process or continuous manufacturing. This sequence reduced overlapping coding and kept E6 as a terminal category for clearly process or continuous manufacturing studies.

Codes E7 and E10 were used only for Google Scholar records because language and document type had already been controlled in Scopus and Web of Science. E8 referred to full-text unavailability, and E9 referred to retracted publications. E1 was expected to appear at title or title-and-abstract screening because it covered studies outside manufacturing. For this reason, no record was excluded with E1 during full-text screening. This result supports the sequential logic of the coding scheme and shows that the earlier screening stages removed clearly non-manufacturing records.

Methodological Rationale

The distinction between the title-and-abstract stage and the full-text stage reflected the evidence available at each stage. Title-and-abstract screening used limited bibliographic evidence, so it was applied as a broad sensitivity-oriented step and retained uncertain records. Full-text screening applied the complete eligibility criteria, including discrete-manufacturing relevance, KPI extractability, operational grounding and methodological sufficiency. This two-stage design reduced the risk of early exclusion and made final inclusion depend on operationally meaningful KPI or EnPI evidence. Final studies had to provide indicators that could be extracted, classified and mapped to the relevant standards.

3.5 Screening Process

The screening process followed the workflow defined in the review protocol. Broad primary searches established initial literature coverage, and refinement searches improved retrieval at machine, process, and line or cell level. After the search stage, records from Scopus and Web of Science were exported, deduplicated, screened in Excel and assessed at full text before final inclusion for extraction. Figure 4 summarizes the primary database screening workflow.

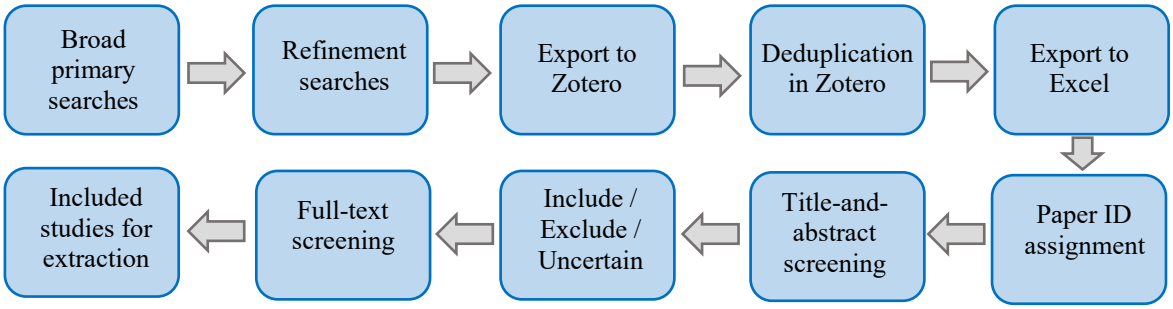

Figure 4. Screening workflow used for records retrieved from the primary databases, Scopus and Web of Science.

For the primary database pathway, records retrieved from Scopus and Web of Science were exported to Zotero for record management and deduplication. The remaining unique records were then exported to Excel, assigned paper IDs, and screened using the predefined categories Include, Exclude, and Uncertain. This stage followed the broad sensitivity-oriented logic described in Section 3.4.

A supplementary screening pathway was used for Google Scholar to identify additional relevant studies beyond the primary database searches. Google Scholar records required an adapted procedure because exported abstracts and metadata were inconsistent. Figure 5 summarizes the supplementary screening workflow.

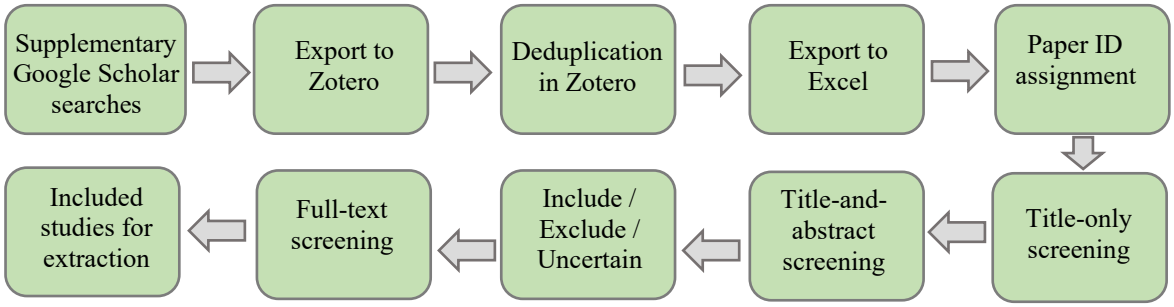

Figure 5. Supplementary screening workflow used for Google Scholar records.

Google Scholar records were imported into Zotero and deduplicated. The remaining records first underwent title-only screening to remove clearly irrelevant records. The retained subset then moved to title-and-abstract screening, where records marked as Include or Uncertain proceeded to full-text assessment.

Full-text screening was the final eligibility stage for both pathways. At this stage, the criteria were applied more strictly to confirm discrete manufacturing relevance, operational level, and the presence of at least one energy KPI or EnPI suitable for structured extraction or standard mapping. Excluded records were assigned one predefined exclusion code, and only eligible studies were retained for data extraction.

3.6 Data Extraction Procedure

This section presents the data extraction procedure used in the review. It explains the KPI-level extraction sheet, extracted fields, KPI eligibility logic, and rule-based KPI-to-standard mapping. These steps supported consistent data representation and later framework development.

3.6.1 Extracted Fields and Data Structure

Data extraction was conducted in a structured spreadsheet at individual KPI level. Paper-level information was retained as bibliographic and source information. This structure was needed because one study could report several indicators with different meanings, inputs, boundaries and analytical roles. A single paper could therefore generate several extraction rows when it reported more than one relevant energy KPI or EnPI. The extraction sheet included paper ID, title, authors, year, citation, source database and KPI-specific fields. Table 4 summarizes its core fields.

Table 4. Core fields used in the data extraction sheet

Field	Purpose
Paper ID	Unique identifier for traceable extraction.
KPI raw name	KPI label reported in the source article.
KPI standardized name	Standardized label for cross-study comparison.
Unit	Reported or clearly derivable KPI unit.
Energy KPI status	Distinguishes direct energy KPIs and EnPIs from supporting KPIs.
Boundary	Operational scope used to measure or interpret the KPI.
Manufacturing level	Production level at which the KPI is located or interpreted.
KPI type	Functional or analytical KPI category.
Data type	Data basis used to derive or report the KPI.
Required inputs	Minimum variables, measurements, or signals for calculation or interpretation.
Input requirement group	Broader grouping of required inputs for analysis.
Calculation method	Method used to derive the KPI value, such as measurement, formula, aggregation, state-based calculation, or model-based estimation.
Formula reported	Explicit formula reported in the source article.
Formula availability	Indicates if the formula was explicit, inferable, or weakly specified.
Main industry context	Main manufacturing context of the source study.
Study Type	Main research approach of the source study.
Standard mapping fields	Standard mentions and mapping results for ISO 50001, ISO 22400 and ISO 20140, including status and basis.
Extractable on real dataset	Indicates if the KPI could be operationalized using the selected real dataset.
Framework role	Analytical role of the KPI in the framework.
Intended use	KPI purpose in the source study, such as monitoring, comparison, optimization, diagnosis, prediction, or improvement.

The field Extractable on real dataset was included to support the later illustrative application step. This field was kept separate from study inclusion, KPI retention, and KPI-to-standard mapping decisions. The value Yes was assigned when the KPI could be operationalized with the selected real dataset without unsupported assumptions. Partial was assigned when the KPI was conceptually interpretable but one or more required variables or implementation details were missing. No was assigned when the KPI could not be defensibly operationalized with the available dataset variables.

In addition to descriptive fields, the extraction procedure included contextual and analytical fields for framework development. These fields included boundary, manufacturing level, KPI type, data type, industry context, and Energy KPI status. The Energy KPI status field distinguished direct energy KPIs and EnPIs from energy-related supporting KPIs and helped organize the extracted indicators by analytical role. The extraction sheet also included fields for framework development and standard interpretation. These fields included framework role and standard mapping fields. The standard mapping fields recorded explicit standard mentions, ISO mapping outcomes, mapping bases, thesis-standard mapping status, standard-linkage type, and mapping notes. To apply these fields consistently across studies, the review defined decision rules for determining when a reported KPI was sufficiently specified for structured extraction.

3.6.2 Decision Rules for KPI Identification and Structured Extraction

After the extraction fields had been defined, each reported indicator was evaluated through a fixed sequence of coding decisions. This step ensured consistent KPI identification, interpretation and documentation before standard mapping.

1. Identification of a KPI candidate: A reported quantity was treated as a KPI candidate when it appeared as a distinct measurable or computable indicator used for monitoring, comparison, evaluation, optimization, diagnosis, prediction, or decision support. Descriptive mentions of energy use, machine behavior, or process conditions were excluded when they did not function as distinct indicators.

2. Interpretation of KPI meaning and scope: Once a KPI candidate had been identified, the related text, tables, figures, equations and method description were examined to determine the indicator meaning, derivation method and operational scope. At minimum, a

KPI had to have a stable reported name or clearly identifiable description, an interpretable measurement meaning, an identifiable boundary or manufacturing level, and either an explicit formula or a defensible calculation logic.

3. Determination of whether the KPI was energy-related: The next decision assessed the energy relevance of the indicator. This decision followed ISO 50001, which defines energy performance in relation to energy efficiency, energy consumption and energy use, and defines an energy performance indicator as a measure or unit of energy performance (ISO 50001 2018). A KPI was treated as energy-related when it directly measured energy consumption, energy use, energy efficiency, specific energy consumption, energy intensity per unit, cycle, batch, or product, power demand, energy loss, energy saving, or another explicit energy performance measure.

4. Assignment of Energy KPI status: After energy relevance had been established, the field Energy KPI status was coded as either Direct energy KPI or EnPI or Energy-related supporting KPI. A KPI was coded as Direct energy KPI or EnPI when it directly quantified energy or an energy-performance relationship. This category included total energy consumption, standby energy, idle energy, cutting energy, component energy consumption, power demand, average power, maximum power, energy efficiency, processing energy efficiency, specific energy consumption and quantified energy loss. A KPI was coded as Energy-related supporting KPI when it supported the interpretation, diagnosis, segmentation, prediction, or contextualization of energy behavior. This category included overall equipment effectiveness, variability measures, coefficients of variation, model error measures, anomaly features, tool-aging factors and other operational or statistical indicators used to support energy-oriented analysis.

5. Completion of extraction fields: After Energy KPI status had been assigned, the remaining core extraction fields were completed in a fixed order. The standardized KPI name was assigned by normalizing the reported label while preserving the original meaning. The unit was recorded as reported, or inferred only when the formula, variable definitions, or calculation description made it unambiguous. Otherwise, it was marked as not reported. Boundary was coded according to the operational entity of the KPI, such as machine-level system, machine subsystem, process step, production line, or broader production system. Manufacturing level was coded as machine, process or unit operation, line or cell, or multi-level. KPI type was assigned according to analytical function, including absolute energy

consumption, power or demand KPI, energy efficiency ratio, specific or intensity-based KPI, improvement or savings KPI, or composite or hybrid KPI. Data type recorded the data basis used to produce the KPI value. Required inputs recorded the minimum variables, measurements, or signals needed to derive the KPI. Calculation method documented the procedure used to obtain the KPI value, such as direct measurement, formula-based calculation, aggregation, decomposition, state partitioning, clustering, or model estimation. Formula reported captured the explicit equation when available. If no closed-form equation was provided, the formula field recorded not explicitly reported, and the computational logic was documented in Calculation method. Intended use recorded the analytical purpose stated in the article, such as monitoring, comparison, predictive maintenance, anomaly detection, energy transparency, scheduling, rescheduling, or improvement assessment.

6. Assignment of Framework role: After the core extraction fields had been completed, the analytical role of the KPI was assigned. This decision was based on intended use, analytical function, dependence on measured or derived energy data, and role in monitoring, interpretation, or decision-making. A KPI was coded as a Decision-layer KPI when it directly supported performance assessment, prioritization, optimization, or decision-making. A KPI was coded as a Measurement-enabling KPI when it provided measured or derived energy information for calculation, disaggregation, or interpretation of higher-level KPIs. A KPI was coded as a Supporting KPI when it provided contextual, operational, diagnostic, or explanatory support for energy-oriented analysis. Indicators without a retained analytical role were coded as Exclude.

Figure 6 summarizes the decision flow used for KPI identification, coding, and preparation for standard mapping.

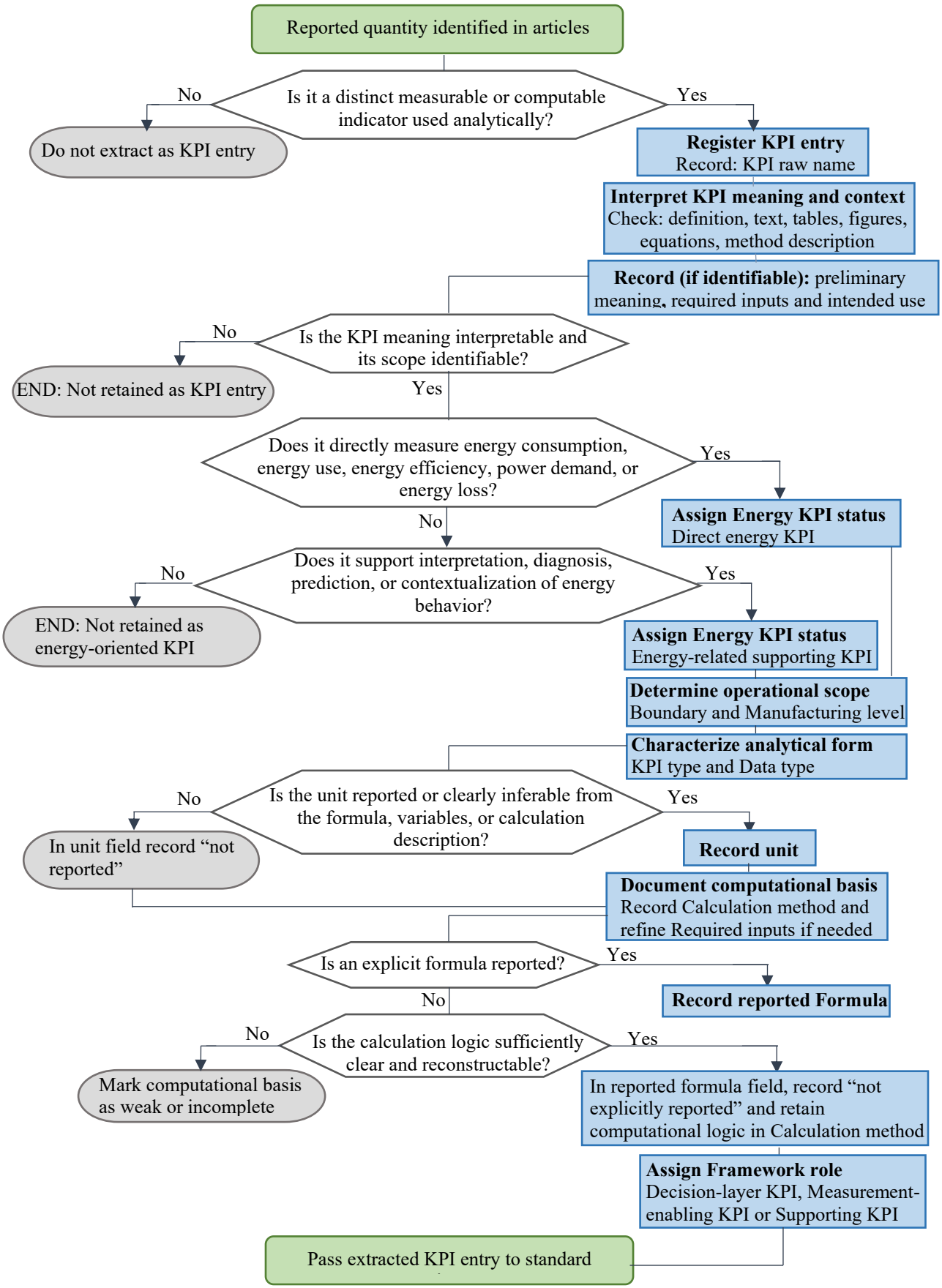

Figure 6. Decision flow for KPI identification, coding, and mapping preparation.

3.6.3 KPI-to-Standard Mapping Procedure

After KPI identification, interpretation, and extractability assessment in Section 3.6.2, each extracted KPI entry was assessed with a structured rule-based mapping procedure. Mapping was conducted at KPI entry level. Each KPI was evaluated based on its definition, formula, required inputs, measurement logic, operational boundary, and reported use. KPI specific standard links were recorded first. These links covered standards connected to the KPI, measurement method, formula, data structure, and calculation context. Article level standard references were recorded only when they were clearly connected to the specific KPI or its direct calculation context. Each KPI was then assessed against ISO 50001, ISO 22400, and ISO 20140. ISO 50001 served as the primary reference for energy performance. ISO 22400 and ISO 20140 served as complementary references for manufacturing operations and environmental manufacturing performance. In this mapping step, insufficient KPI detail meant insufficient detail for defensible standard alignment. This label described the mapping decision and remained separate from the extraction decision.

For ISO 50001, a KPI was mapped when it represented energy performance or directly supported its assessment. The KPI had to be quantifiable, energy-related, and usable for monitoring, comparison, benchmarking, baseline comparison, savings assessment, prediction, or improvement. It also had to have a defined operational boundary and a defensible formula or reconstructable calculation logic. Mapped KPIs were assigned one basis from the predefined categories, Energy performance and EnPI logic, Energy baseline and comparison logic, measured energy data required, or Supporting metric only. Supporting metric only was used when a KPI was needed to calculate, normalize, decompose, or interpret an energy KPI. KPIs with no relevant link to ISO 50001 were recorded as Not relevant to this standard. KPIs with a possible link and weak formula, input, unit, boundary, measurement, or use context were recorded as Insufficient KPI detail. Table 5 defines the mapping basis categories used for ISO 50001 alignment.

Table 5. Mapping-basis categories used for ISO 50001 alignment.

Mapping outcome	Mapping basis	Application rule
Yes	Energy performance and EnPI logic	Used when the KPI directly represents energy performance, such as energy consumption, power demand, energy efficiency, or energy loss.
Yes	Energy baseline and comparison logic	Used when the KPI supports baseline comparison, before-and-after comparison, expected-versus-observed energy comparison, or savings assessment.
Yes	Measured energy data required	Used when the metric is directly based on measured energy or power data and supports energy monitoring.
Yes	Supporting metric only	Used when the metric is not the main EnPI but is directly needed to calculate, normalize, decompose, or interpret an energy KPI.
No	Insufficient KPI detail	Used when the article mentions a potentially relevant energy metric but lacks sufficient formula, unit, input, boundary, or calculation detail.
No	Not relevant to this standard	Used when the metric is not related to energy management or energy performance.

For ISO 22400, a KPI was mapped when it represented production performance or manufacturing operations performance. Technical inputs, model parameters, and calculation variables were excluded from ISO 22400 mapping. Mapped KPIs were assigned one basis from the predefined categories, Production performance KPI, Manufacturing operations KPI, or Supporting metric only. Supporting metric only was used when a KPI directly supported the calculation or interpretation of an operational performance KPI. KPIs with no relevant link to ISO 22400 were recorded as Not relevant to this standard. KPIs with a possible link and weak detail were recorded as Insufficient KPI detail. Table 6 presents the mapping basis categories used for ISO 22400 alignment.

Table 6. Mapping-basis categories used for ISO 22400 alignment.

Mapping outcome	Mapping basis	Application rule
Yes	Production performance KPI	Used when the KPI directly measures production performance, such as OEE, availability, quality, throughput, or production rate.
Yes	Manufacturing operations KPI	Used when the KPI represents manufacturing-operation behavior, such as utilization, cycle time, idle time, operation time, or scheduling performance.
Yes	Supporting metric only	Used when the metric is not the main production or operations KPI but directly supports its calculation or interpretation.
No	Insufficient KPI detail	Used when the article mentions a production or operations metric but lacks sufficient detail for defensible mapping.
No	Not relevant to this standard	Used when the metric does not represent production-performance or manufacturing-operations performance.

For ISO 20140, mapping was applied only when the KPI represented environmental or resource-related manufacturing performance beyond ordinary energy monitoring. When mapped, the basis was recorded as Environmental manufacturing performance, Life-cycle and process environmental assessment, or Supporting metric only. Supporting metric only was used only when the KPI was explicitly required to interpret or calculate an environmental manufacturing performance measure. Energy consumption, power demand, SEC, and energy cost were not automatically mapped to ISO 20140 unless the source article framed them as environmental performance, resource efficiency, emissions assessment, or process environmental impact. KPIs that were unrelated or insufficiently defined were recorded as Not relevant to this standard or Insufficient KPI detail, respectively. Table 7 defines the mapping-basis categories used to assess whether an extracted KPI entry could be interpreted in relation to ISO 20140 as an environmental manufacturing performance reference.

Table 7. Mapping-basis categories used for ISO 20140 alignment

Mapping outcome	Mapping basis	Application rule
Yes	Environmental manufacturing performance	Used when the KPI directly measures environmental manufacturing performance or environmental burden, such as carbon emission, resource consumption, waste, or scrap.
Yes	Life-cycle and process environmental assessment	Used when the KPI is applied in life-cycle, product-level, process-level, or environmental assessment.
Yes	Supporting metric only	Used when the metric is not itself an environmental KPI but directly supports the calculation or interpretation of one.
No	Insufficient KPI detail	Used when the article mentions an environmental or energy-related metric but lacks sufficient calculation detail, unit, input data, or boundary information.
No	Not relevant to this standard	Used when the metric has no explicit environmental or resource-assessment link.

All mapping decisions were based only on information available in the source article. No mapping was assigned based on unsupported assumptions. The rule-based decision process used to determine KPI-to-standard mapping outcomes is illustrated in Figure 7.

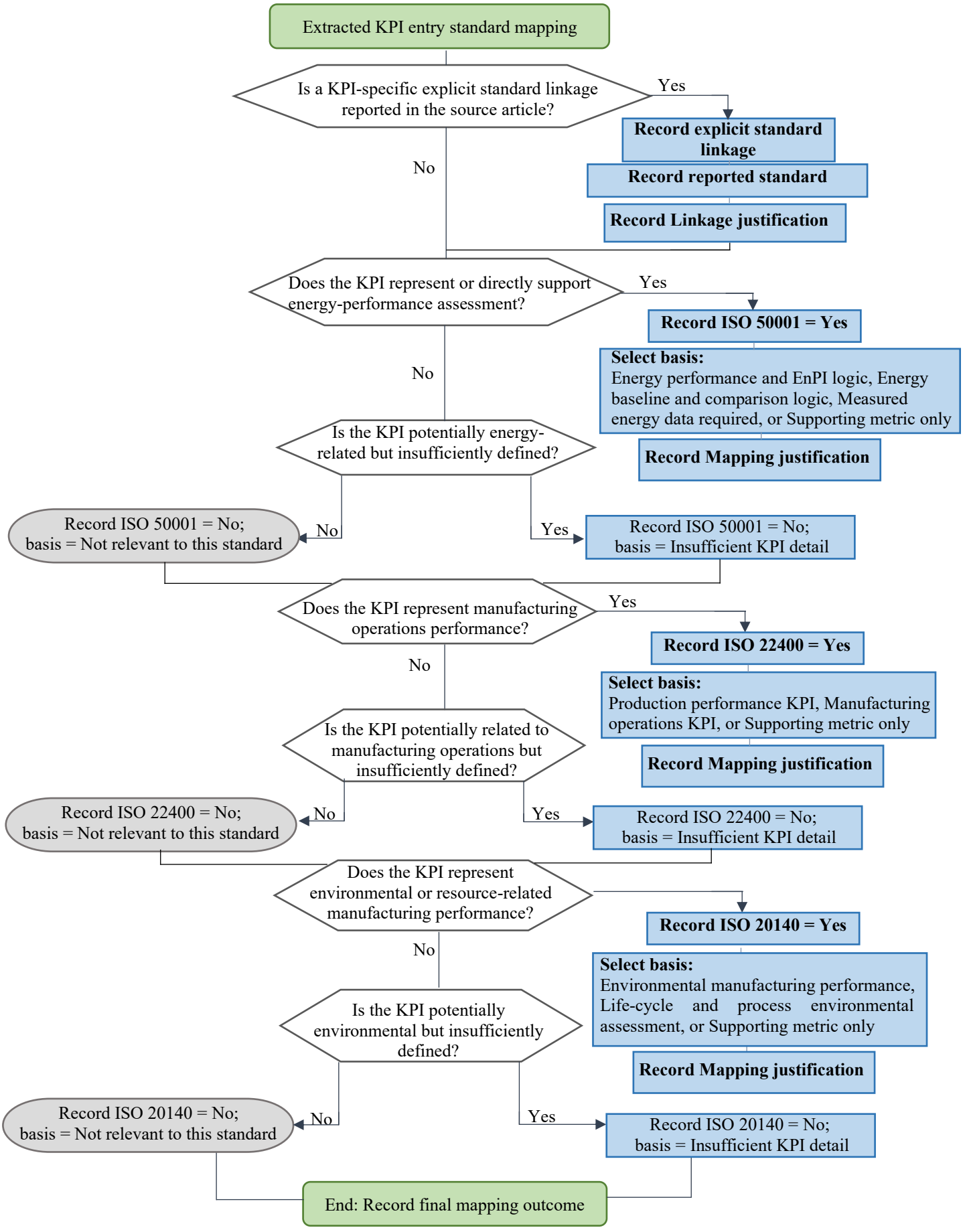

Figure 7. Decision flow for rule-based KPI-to-standard mapping.

3.7 KPI Classification Framework

The KPI classification framework organized the extracted KPI entries into a consistent structure. This was needed because the reviewed studies reported energy-related indicators with different scopes, levels, calculation forms, data bases, and intended uses. Energy indicators can be used at different aggregation and decision levels, so their interpretation depends on defined boundaries and purposes (Benedetti et al. 2017). One general EnPI is unsuitable for all manufacturing contexts because relevant variables and boundary levels differ across cases (Kanchiralla et al. 2020). For this reason, this thesis used a higher level classification framework to organize KPI evidence in a consistent and interpretable form.

The framework was derived from the KPI entry level extraction process. The extraction fields showed recurring dimensions needed for interpretation, including Energy KPI status, KPI type, boundary, manufacturing level, data type, and framework role. In this chapter, these dimensions are defined as methodological classification dimensions. Chapter 5 presents the detailed synthesis of KPI groups based on these dimensions. The framework has four main dimensions. The conceptual dimension separates direct energy KPIs and EnPIs from energy-related supporting KPIs. The analytical dimension is KPI type. The contextual dimensions are operational boundary, manufacturing level, and data type. The interpretive dimension is framework role. Figure 8 presents the structure of these four dimensions.

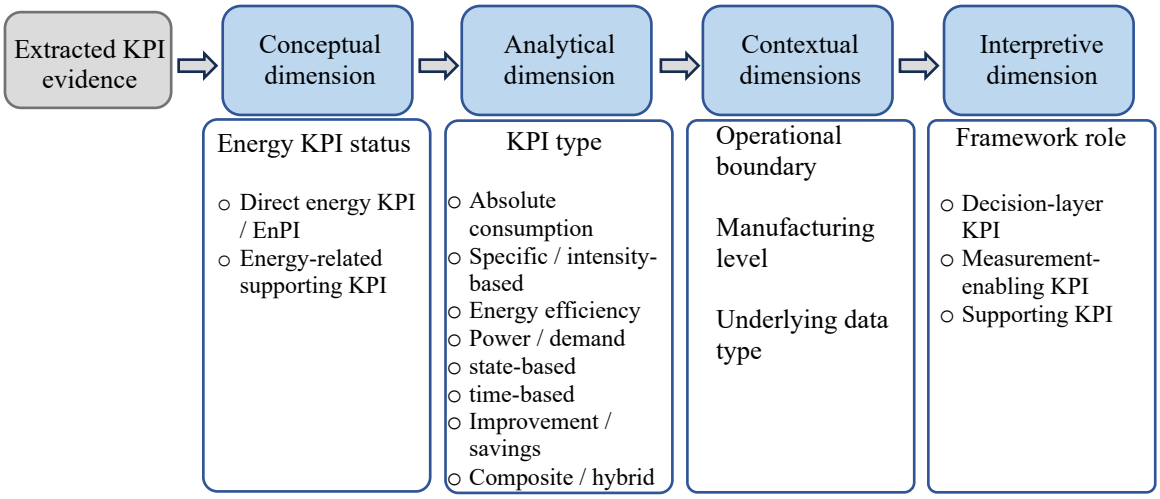

Figure 8. Multi-dimensional KPI classification framework used to organize extracted KPI evidence through conceptual, analytical, contextual, and interpretive dimensions.

3.7.1 KPI type as Analytical Dimension

EnPIs can be described in broad forms, including direct energy use, ratio-based indicators, and model-based representations. These broad forms give a useful conceptual basis, but they are too general for comparing the KPI definitions extracted in this review. They also do not capture all recurring KPI forms found in the reviewed studies (Kanchiralla et al. 2020).

For this reason, this thesis uses KPI type as an analytical dimension. Absolute energy consumption was retained as a separate type because it gives the most direct measurable form of energy use. Ratio based indicators were divided into specific and intensity based KPIs and energy efficiency ratios because normalization by output and efficiency relations have different analytical meanings. Composite and hybrid KPIs were linked to model-based representations because they combine variables or depend on modeled relations. Additional types were added when recurring KPI forms in the reviewed studies were outside the broad typology. These types include power and demand KPIs, state based KPIs, time based KPIs, and improvement and savings KPIs. In this thesis, KPI type defines the representation of energy performance and supports consistent grouping and comparison across studies. Table 8 presents the alignment between the EnPI characteristics discussed by Kanchiralla et al. and the KPI type dimension used in this thesis.

Table 8. Alignment between broad EnPI characteristics and the KPI type dimension

Kanchiralla et al. characteristic	KPI type in this thesis	Type of relationship
Energy use	Absolute energy consumption	Direct refinement
Ratio-based indicator	Specific or intensity-based KPI	Refined subdivision
Ratio-based indicator	Energy efficiency ratio	Refined subdivision
Model-based representation	Composite or hybrid KPI	Conceptual alignment
Not explicitly distinguished	Power and demand KPI	Analytical extension
Not explicitly distinguished	State-based energy KPI	Analytical extension
Not explicitly distinguished	Time-based energy KPI	Analytical extension
Not explicitly defined as form	Improvement and savings KPI	Functional extension

Table 8 shows that the KPI type dimension in this thesis builds on the broad EnPI characteristics and extends them into more detailed categories needed for comparison across the reviewed studies.

3.7.2 Boundary as a Contextual Dimension

In this thesis, contextual dimensions were included because energy KPI meaning requires more than the KPI label. The same KPI name, such as energy consumption or specific energy consumption, may refer to different operational scopes and support different types of analysis depending on its application context. Energy indicators are used at different aggregation and decision levels, so their usefulness depends on defined boundaries and appropriate scope (Benedetti et al. 2017). Relevant variables and boundary level also need to be considered when developing energy performance indicators (Kanchiralla et al. 2020). For this reason, boundary and manufacturing level were retained as separate contextual dimensions. Boundary identifies the operational entity of the KPI. Manufacturing level identifies the hierarchical production level at which the KPI is interpreted.

Within this framework, boundary was treated as a core contextual dimension because KPIs with similar analytical form may refer to different physical or operational entities. This affects KPI interpretation, comparison, and later linkage to decision making. The boundary categories were formalized from recurring KPI scopes observed across the reviewed studies.

Individual machine was retained for KPIs assigned to one identifiable asset as a whole, such as total energy consumed by Machine Mi (Zhang et al. 2020). Machine subsystem was retained for component level KPIs, such as spindle drive power or component energy consumption (Panten et al. 2016). Machine level system captured cases where the whole machine was treated as an integrated operating system, which is consistent with EnPI boundary distinctions between individual and system levels (Kanchiralla et al. 2020). Process step and unit operation were retained for KPIs linked to production states or process phases, such as standby, idle, air cutting, and cutting (Zhang et al. 2020). Production line was retained for line wide KPIs, especially energy loss or total line consumption across connected operations (Nota et al. 2020). Multi-level and not reported were retained to keep coding transparent for cross boundary or unclear cases. These categories preserve the operational scope of each KPI and reduce misinterpretation during comparison across studies (Benedetti et al. 2017). Table 9 presents the boundary categories used in this thesis and shows their meaning, rationale for inclusion, and role in the framework.

Table 9. Boundary categories used in this thesis

Boundary type	Meaning	Why retained in this thesis	Role in the framework
Individual machine	One identifiable machine treated as a standalone asset	Needed for KPIs reported for one specific machine as a whole	Supports asset-level interpretation and comparison
Machine subsystem	A component or module within a machine	Needed for disaggregated KPIs such as spindle, drive, motor, or component energy	Captures sub-machine energy behavior
Machine-level system	A machine treated as an integrated operating system	Needed where the KPI refers to the overall machine system rather than only a physical asset	Preserves system-oriented interpretation of machine-level KPIs
Process step	A specific step or phase within a process	Needed for KPIs linked to standby, idle, cutting, air-cutting, or other step-specific states	Supports process-phase interpretation
Unit operation	A functional production operation	Needed where the KPI is defined at operation level rather than at whole-machine level	Captures operation-oriented scope
Production line	A connected production line	Needed for line-wide KPIs such as line energy loss or total line consumption	Supports broader system comparison across multiple operations
Work cell	A local group of machines or workstations	Retained for intermediate scopes smaller than a full line	Preserves meso-level operational scope
Multi-machine system	A grouped set of machines not necessarily forming a full line	Retained for studies using grouped-machine boundaries	Captures aggregated machine-group scope
Multi-level	More than one boundary is analytically central	Needed to avoid oversimplifying KPIs spanning multiple scopes	Preserves cross-boundary interpretation
Not reported	Boundary not clearly stated in the article	Needed to keep coding transparent instead of forcing assumptions	Maintains methodological consistency

3.7.3 Manufacturing Level as a Contextual Dimension

The general meaning of contextual dimensions and the distinction between boundary and manufacturing level were introduced in Section 3.7.2. This subsection focuses on the rationale for selecting the manufacturing level categories and their analytical role in the framework. Manufacturing level was retained to capture the hierarchical level at which a KPI is interpreted in the production system. Energy indicators are used at different aggregation and decision levels, which supports their interpretation as different levels of analysis (Benedetti et al. 2017). Manufacturing systems can also be interpreted as hierarchical structures extending from device or unit process level to line or cell level, which supports retaining line or cell as a separate category (Nota et al. 2020).

Process or unit operation was retained for KPIs interpreted at the level of specific states or process phases, such as standby, idle, air cutting, and cutting. The machine category was retained for KPIs interpreted around the operation of a specific machine, such as total machine energy, machining energy, and waiting energy (Zhang et al. 2020). Multi-level was retained for KPIs that span more than one production level. Not reported was retained to avoid unsupported assignments. Table 10 presents the manufacturing level categories used to interpret KPIs according to their hierarchical position in the production system.

Table 10. Manufacturing-level categories used in this thesis

Manufacturing level	Meaning	Why retained in this thesis	Role in the framework
Machine	KPI interpreted at the level of a single machine or its overall operation	Needed for machine-oriented monitoring and energy-performance assessment	Supports asset-level comparison across studies
Process or Unit operation	KPI interpreted at step, state, or operation level	Needed for process-state and operation-specific KPIs such as idle, standby, cutting energy and air-cutting	Preserves fine-grained operational meaning
Line or Cell	KPI interpreted across a coordinated production structure of multiple machines or stations	Needed for line-wide or cell-wide performance and energy-loss analysis	Supports broader production-system comparison
Multi-level	KPI analytically relevant across more than one production level	Needed when one fixed level would oversimplify the KPI meaning	Prevents forced simplification
Not reported	Level not clearly inferable from the source	Needed to preserve transparency instead of making assumptions	Maintains coding consistency

3.7.4 Data Type as a Contextual Dimension

The general role of contextual dimensions has been introduced in the previous subsections. This subsection explains the reason for retaining data type as a separate contextual dimension. Data type was retained because the same KPI can be based on different forms of evidence. This affects interpretation, comparison, and later use in the framework. Reliable energy analysis depends on monitoring data, data collection, synchronization, and reporting frequency, so KPI interpretation depends on the indicator label and the structure of the supporting data (Benedetti et al. 2017). Manufacturing energy analysis can rely on measured operational data, processed features, and combined datasets (Zhang et al. 2020). Accordingly, data type in this thesis was treated as the evidential basis used to measure, derive, or support a KPI.

The selected data type categories were organized analytically. Time-resolved measured data was retained because it supports load profiles, process state segmentation, and dynamic energy interpretation. This role appears in studies where continuous energy data are partitioned by process and reduced into state specific features (Zhang et al. 2020). It also appears when aggregate machine power and control signals are used to infer component level energy consumption (Panten et al. 2016). Recorded operational data was retained because event logs and production records connect energy data with machines, workpieces, and process stages. Aggregated and summarized data was retained for KPIs reported at batch, interval, or line summary level, including energy loss accounting and block based energy calculation (Nota et al. 2020). Derived and indirect data was retained because many KPIs are constructed from monitored data, as seen in life cycle oriented machining energy quantities (Wang et al. 2018). These categories help the framework distinguish the KPI measurement target from the evidence behind it. This distinction supports comparability, extractability, and later interpretation. Table 11 presents the data type groups used in this thesis and shows their meaning, rationale for retention, and role in the framework.

Table 11. Data-type categories used in this thesis

Data type group	Included categories	Meaning	Why retained in this thesis	Role in the framework
Time-resolved measured data	Time-series continuous; Time-series sampled; State-based; Cycle-based; Batch-based	Data captured over time, either continuously or in operational segments	Needed for dynamic KPIs such as power, state energy, and process-segment energy	Supports detailed operational interpretation
Recorded operational data	Event log; Production record; Maintenance record; Labelled condition data; Count based records	Process or execution records that describe events, states, counts, or conditions	Needed to connect energy data with process context and machine or workpiece events	Supports contextual interpretation and data association
Aggregated and summarized data	Aggregated interval; Aggregated summary; Audit or baseline dataset	Data already combined over intervals, batches, or reporting periods	Needed for KPIs reported at higher summary level rather than raw signal level	Supports broader comparison and baseline-oriented interpretation
Derived and indirect data	Derived and calculated; Simulation output; Image-derived; document-derived; Hybrid; Not reported	Data obtained through calculation, modelling, secondary extraction, or mixed evidence	Needed because many KPIs are analytically constructed rather than directly measured	Supports traceability of evidential basis and extractability assessment

3.7.5 Framework Role as an Interpretive Dimension

Following the coding logic established in Section 3.6.2, framework role was used as an interpretive layer to clarify the function of each KPI in the framework. This was needed because indicators with similar analytical form could serve different functions in the

reviewed studies. In this thesis, KPI type describes the analytical construction of a KPI. Framework role describes its function in monitoring, interpretation, and decision making. A KPI was assigned to the Decision-layer role when it directly supported performance assessment, comparison, prioritization, optimization, scheduling, rescheduling, or improvement action. This role is visible when total machine energy, machining energy, and waiting energy are used for rescheduling and multi-objective optimization (Wang et al. 2018). It is also visible when energy efficiency and processing energy efficiency are used for evaluating and comparing machine tool performance (Zhang et al. 2020).

A KPI was assigned to the Measurement-enabling role when it mainly provided measured or derived energy evidence for profiling, segmentation, disaggregation, transparency, or downstream KPI construction. This role provides the measurement basis for later interpretation. Aggregate machine power and component level power demand show this role because they support fine grained monitoring and component level transparency (Panten et al. 2016). Electrical load profile shows the same role because it provides the data source for process monitoring, order tracking, and later interpretation. In that case, derived descriptors such as average, maximum, minimum, and median power provide interpretable comparative figures (Wächter et al. 2025).

A KPI was assigned to the Supporting role when it provided contextual, diagnostic, statistical, or explanatory support for analysis of energy behavior. This role covers indicators that support interpretation without serving as the main decision variable or measurement basis. OEE shows this role because it structures operational losses and supports energy-oriented interpretation. Variability and anomaly features show the same supporting function (Nota et al. 2020). In the E-CPS study, statistical features extracted for different machine states were used as input features for recessive production anomaly detection based on a Deep Belief Network (DBN). Max, Mean, and Vari refer to maximum, mean, and variance values. This use supports their classification as Supporting KPIs (Zhang et al. 2020).

Energy quantities linked to states required role assignment based on their use in the source study. They were coded as Decision-layer KPIs when they served as standalone indicators of productive or idle energy performance. They were coded as Supporting KPIs when they appeared as components or analytical features in optimization or anomaly detection. This rule clarified the role of each indicator as a decision metric, measurement basis, or

explanatory support. Table 12 presents the framework role categories, their assignment basis, and representative examples.

Table 12. Framework role categories used in this thesis

Framework role	Core meaning	Main assignment basis	Example
Decision-layer KPI	KPI directly used for performance judgement or action	assessment, comparison, prioritization, optimization, scheduling, rescheduling	SEC, DI, E_{total}(Mi)
Measurement-enabling KPI	KPI providing measured or derived energy evidence for higher-level interpretation	monitoring, profiling, segmentation, disaggregation, transparency	aggregate machine power demand, electrical load profile
Supporting KPI	KPI providing contextual, diagnostic, variability-related, or explanatory support	anomaly analysis, variability interpretation, model support, contextualization	OEE, CV, MAPE, tool aging factor
Exclude	Indicator not retained within the final analytical framework	no defensible retained energy-oriented role	non-retained indicator

Figure 9 presents the logic used to assign framework role after KPI type, boundary, manufacturing level, data type, and intended use had been coded.

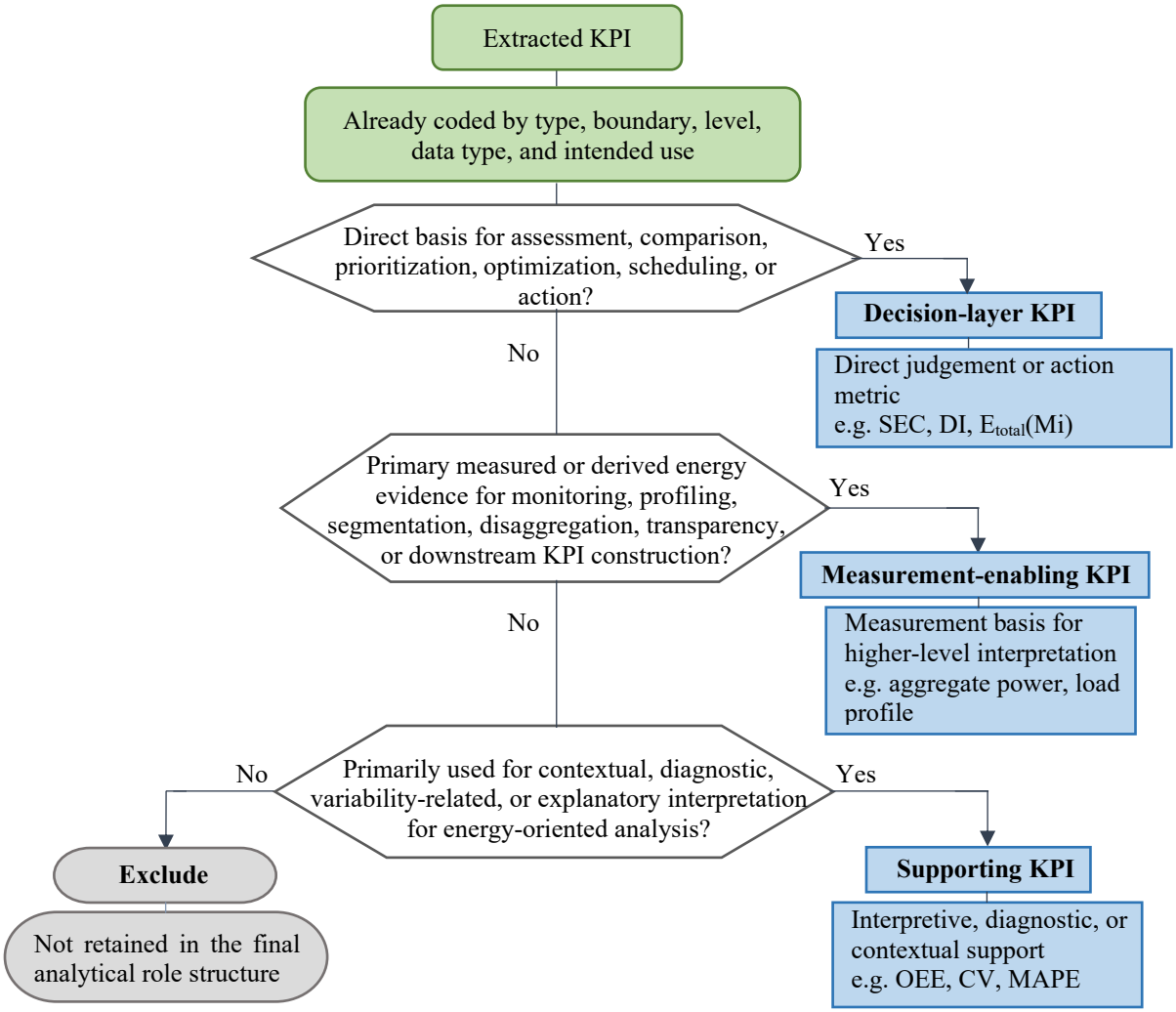

Figure 9. Rule-based logic used to assign framework role to extracted indicators in the proposed KPI classification framework.

3.8 Limitations of the Methodology

This methodology has several limitations. First, KPI extraction depended on the quality and clarity of the published studies. Because the framework used reported evidence, extraction depended on how clearly each article described the KPI name, boundary, inputs, calculation logic, and intended use. Incomplete elements required structured interpretation of the published text. Direct recomputation or verification from raw data was not possible.

Second, the reviewed literature was highly heterogeneous. The studies used different terms, analytical detail, reporting formats, operational boundaries, and ways of using energy-related indicators. Conceptually close indicators therefore did not always have the same name, and similar names did not always indicate the same analytical role. This diversity supports the need for a unified framework and limits perfect comparison across studies.

Third, study retrieval was limited by database coverage, indexing quality, and source terminology. The search process was thorough and well documented, but some relevant studies may have been missed after the structured search and screening procedure.

Fourth, some coding choices remained borderline even with rule-based assignment. This was visible when indicators with similar analytical forms served different functions across studies. Role assignment therefore required judgement based on intended use, analytical position, dependence on measured evidence, and direct interpretability for action or assessment. The rule-based procedure reduced arbitrariness, but interpretive judgement remained part of coding.

A further limitation concerns the framework scope. It was developed for energy-related KPIs in discrete manufacturing at machine, process, or line level, and for studies with sufficient information for computable-based extraction. Direct transfer to process industries, building energy systems, enterprise level indicator systems, or studies based on simulation would require comparable operational grounding.

Finally, the empirical application was constrained by scale. The framework was demonstrated with one real operational dataset. This indicates practical feasibility, but it does not demonstrate generalizability across all manufacturing settings, machine types, or data environments. The application therefore represents a feasibility demonstration, not evidence of universal robustness.

4 Results of the Systematic Review

This chapter presents the results of the systematic review. It first summarizes the selected studies and then analyzes the extracted KPI entries across classification, mapping, data, calculation, and framework role dimensions.

4.1 Overview of the Selected Studies

This section provides an overview of the 76 studies selected in the systematic review. The analysis examines their distribution over time, manufacturing context, and study type to characterize the final dataset before KPI level analysis. The search period was limited to 2015 to 2026 to focus on recent developments linked to Industry 4.0 and data driven manufacturing. The detailed article level information for all selected studies is provided separately (Appendix 5). Figure 10 presents the distribution of selected studies by publication year and manufacturing context.

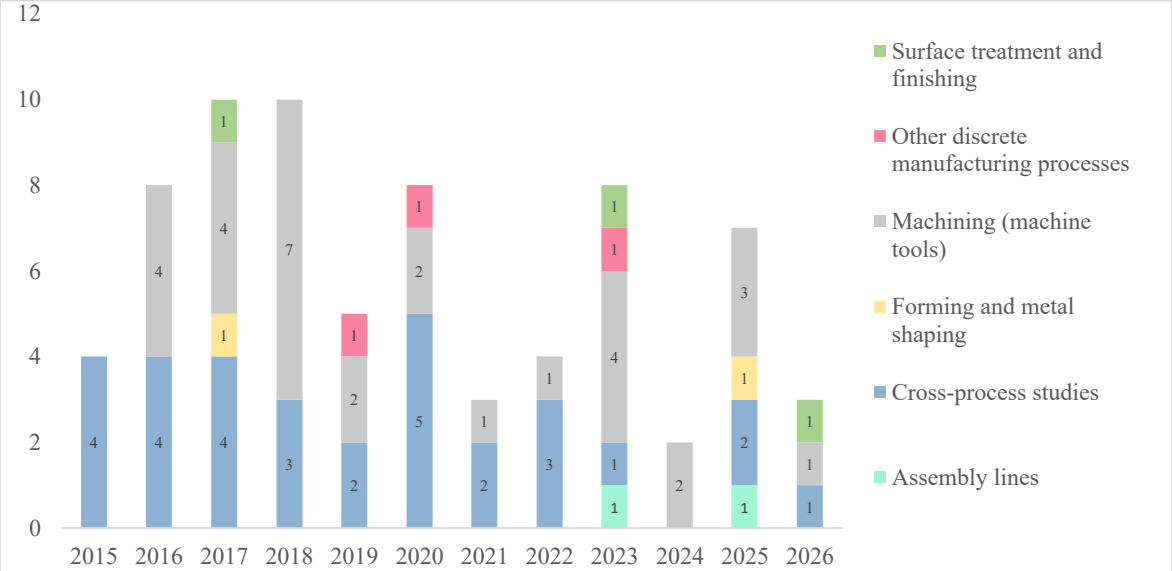

Figure 10. Distribution of selected studies by publication year and manufacturing context.

The studies are distributed across 2015 to 2026, indicating continued research interest in issues related to energy in discrete manufacturing. Four studies had no clearly identifiable manufacturing context because they focused mainly on general method or framework development. These studies were excluded from Figure 10, which includes only studies with

an identifiable manufacturing context. For the remaining studies, manufacturing context was assigned based on the dominant process or production setting. Machining and machine tool studies covered CNC machines, milling, turning, grinding, and related operations. Assembly lines covered assembly systems, production cells, and connected workstations. Forming and metal shaping covered rolling, forming, and related metal processing. Surface treatment and finishing covered cleaning, drying, pickling, and similar operations. Cross process studies covered more than one production process, workshop setting, or broader manufacturing system. Other discrete manufacturing processes covered studies that belonged to discrete manufacturing and did not fit the main process categories.

Regarding manufacturing context, the studies are concentrated mainly in machining and machine tool settings. Cross process studies are also represented, while forming, surface treatment, assembly, and other discrete manufacturing contexts appear less often. This shows that the final dataset is not limited to one industrial context, although it is more strongly oriented toward machine and process level manufacturing environments. This distribution is important for the thesis because studies at these levels often report measurable variables, clearer operational boundaries, and directly applicable energy indicators. Cross process studies broaden the contextual coverage of the review and support a wider interpretation of energy KPI use in discrete manufacturing. Figure 11 presents the distribution of the selected studies by study type.

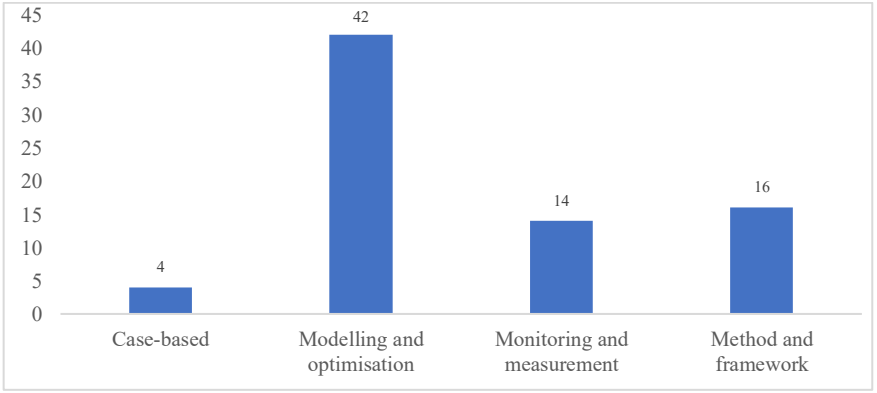

Figure 11. Distribution of studies by study type.

Figure 11 shows that modelling and optimization dominate the selected studies. Fewer studies address monitoring and measurement, method and framework development, or case analysis. This distribution shows a strong focus on analytical and predictive modelling of energy consumption. Modelling studies often introduce energy metrics, and these metrics are usually embedded in specific models. This makes comparison across manufacturing

contexts difficult. The lower number of monitoring and measurement studies shows that fewer works focus on directly measurable indicators from real operational data. The limited number of method and framework studies also shows a lack of structured approaches for organizing and standardizing energy performance indicators. Overall, this distribution supports the need for a structured and standard-aligned framework that connects model-based indicators with measurable and comparable indicators in discrete manufacturing.

4.2 Distribution of Direct and Supporting Energy KPIs

This section analyzes the extracted energy-related KPIs from the 76 selected studies. It focuses on the distinction between direct energy KPIs and supporting energy-related KPIs across manufacturing contexts. The purpose is to examine the frequency of these two KPI roles and their relative balance. This shows the balance between direct measurement and contextual or operational support in energy performance interpretation. Figure 12 presents the average number of direct and supporting energy KPIs per paper across industry contexts.

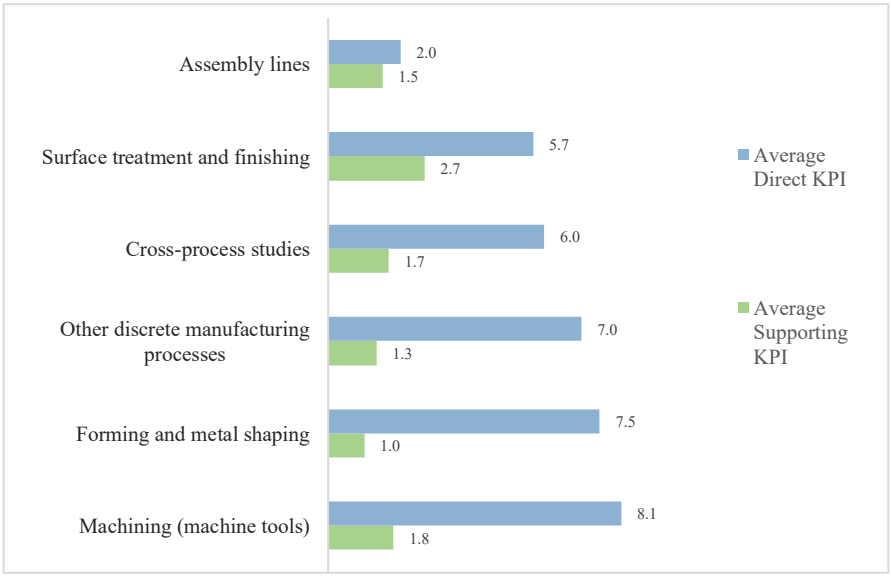

Figure 12. Average number of direct and supporting energy KPIs per paper across industry contexts.

Figure 12 shows that direct energy KPIs outnumber supporting KPIs across all industry contexts. This indicates that the reviewed literature is mainly oriented toward directly measurable indicators, such as energy consumption, power demand, and energy efficiency. Supporting KPIs appear less often and mainly support energy performance interpretation. The difference is clearest in machining and forming contexts, where direct KPIs are high

and supporting KPIs are fewer. Assembly studies show fewer direct KPIs and a smaller gap between the two KPI roles. Since Figure 12 reports average counts per paper, Figure 13 presents the proportional distribution of direct and supporting energy KPIs across industry contexts.

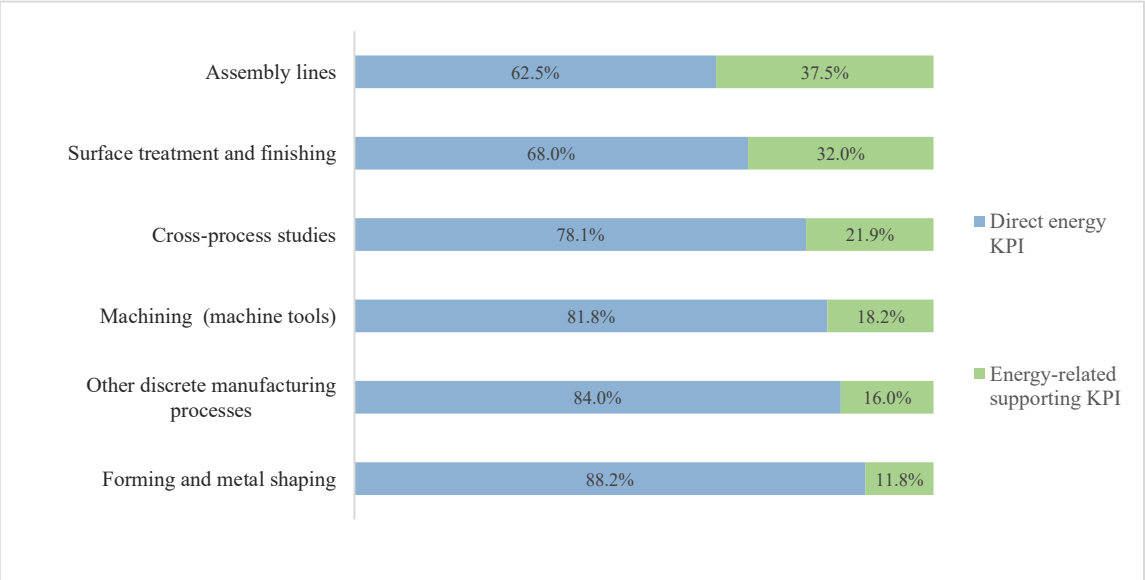

Figure 13. Proportional distribution of direct and supporting energy KPIs across manufacturing contexts.

Figure 13 confirms that direct KPIs dominate across industry contexts, but the degree of dominance differs. Forming and metal shaping shows the strongest direct KPI orientation, with 88.2% direct KPIs. Other discrete manufacturing processes and machining also show strong direct orientation, with 84% and 81.8% direct KPIs. These contexts mainly define energy performance through measurable indicators, including energy consumption, power demand, and efficiency related measures.

Assembly lines and surface treatment and finishing show higher shares of supporting KPIs, with 37.5% and 32%, respectively. Direct KPIs still represent the majority in these contexts but supporting KPIs appear more often to explain energy performance through production flow, process conditions, quality requirements, or auxiliary operational factors. Cross process studies occupy an intermediate position, with 78.1% direct KPIs and 21.9% supporting KPIs. This shows that broader manufacturing system studies still prioritize direct measurement and use supporting indicators to connect energy use with operational conditions across processes.

Taken together Figures 12 and 13 show that direct energy KPIs dominate the reviewed literature by average count and proportional share, although supporting KPI shares differ across manufacturing contexts. This finding contributes to RQ1 by showing that reported energy KPIs include direct energy measures and supporting indicators for energy performance interpretation. It supports RQ2 by confirming the need to separate direct energy KPIs from energy-related supporting KPIs in the taxonomy.

4.3 Manufacturing Levels Addressed by the Extracted Energy KPIs

This section analyzes the distribution of KPI types across manufacturing levels. This analysis is important because the meaning and usefulness of an energy KPI may change across machine, process or unit operation, and line or cell levels. Before presenting the distribution, some KPI categories were consolidated for clarity. Not clearly defined KPIs, state-based energy KPIs, and time-based energy KPIs were grouped under Other. Specific or intensity-based energy KPIs and energy efficiency ratios were grouped under Efficiency and intensity because both describe normalized energy performance. Figure 14 presents the distribution of extracted energy KPI types across manufacturing levels. KPIs coded as multi-level or not reported (n = 5) were excluded from Figure 14 because their small number did not support meaningful comparison with the three main manufacturing levels.

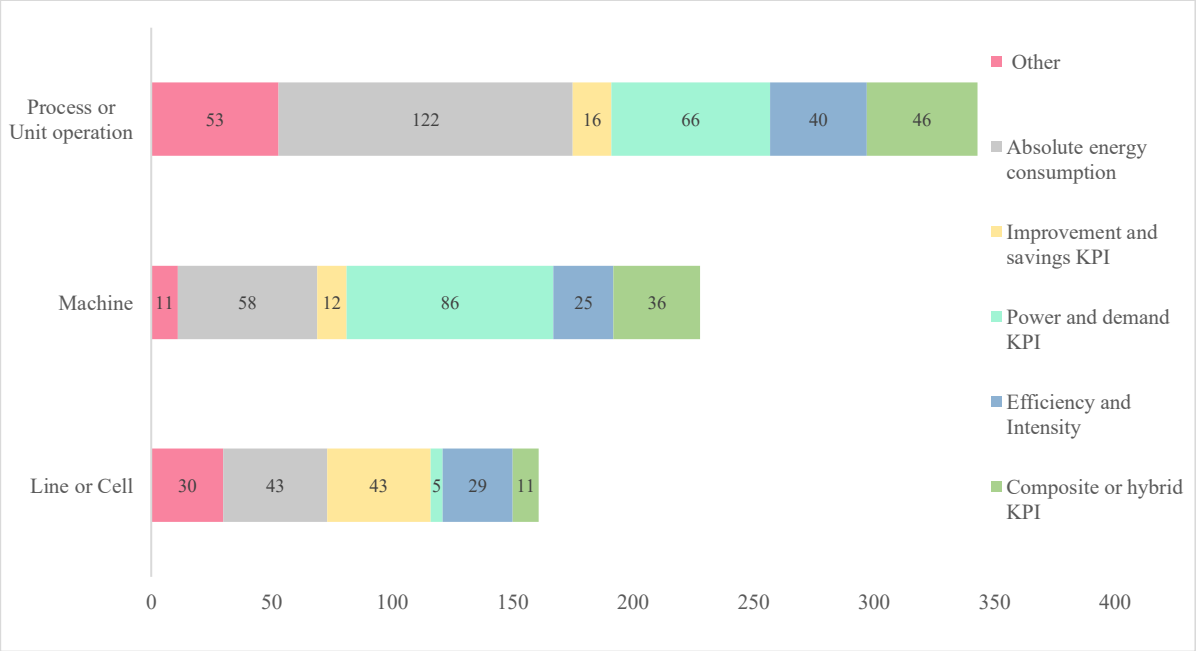

Figure 14. Distribution of extracted energy KPI types across manufacturing levels.

Figure 14 shows that KPI types are unevenly distributed across manufacturing levels. The process or unit operation level contains the largest number of extracted KPIs and the widest variety of KPI types. Absolute energy consumption is the most frequent category at this level, followed by power and demand KPIs, other KPI types, composite or hybrid KPIs, and efficiency and intensity indicators. This suggests that analysis at process level gives the richest operational view because energy use can be linked to process steps, activities, and measurable production conditions.

At the machine level, the distribution is mainly measurement oriented, but power and demand KPIs dominate. This indicates that studies at machine level focus on directly observable energy behavior, such as power profiles, load states, and equipment operating conditions. At the line or cell level, KPI counts are lower, and improvement and savings KPIs are more visible. This result reflects aggregation at line level, as energy performance is often evaluated through production outcomes, reduction potential, and operational improvement.

Overall, Figure 14 shows that manufacturing level is an interpretive dimension of energy KPI analysis. Process or unit operation KPIs provide the widest representation of energy performance. Machine level KPIs are closely linked to direct monitoring and equipment behavior. Line or cell KPIs tend to reflect aggregated performance and improvement-oriented evaluation. This finding contributes to RQ1 by showing that reported energy KPIs differ across production levels. It supports RQ2 by confirming the need to include manufacturing level as a contextual dimension in the taxonomy.

4.4 Measurement Boundaries of the Extracted Energy KPIs

Building on Section 3.7.2, this section examines the measurement boundaries assigned to the extracted energy KPIs. In this thesis, measurement boundary refers to the operational scope included in KPI calculation. Manufacturing level refers to the hierarchical production level at which the KPI is interpreted. This distinction is important because similar KPI names may carry different meanings across operational scopes. For example, an energy consumption KPI defined for an individual machine differs from one defined for a process step, production line, or supporting subsystem. Boundary definition affects KPI interpretation, comparability, and standard-aligned energy performance assessment. This is

consistent with ISO 50001, which emphasizes scope, boundaries, EnPIs, and monitoring procedures in energy management systems (ISO 50001 2018).

To examine the variation of KPI roles across measurement boundaries the extracted indicators were grouped into direct energy KPIs and energy-related supporting KPIs for each boundary category. Figure 15 presents the proportional distribution of these two KPI roles across the main measurement boundaries identified in the extraction dataset. Multi-level, multi machine system, and not reported categories were excluded to compare defined boundary types. These categories either span multiple boundaries, represent grouped-machine configurations, or lack sufficient boundary specification, and therefore did not provide meaningful additional insight for this comparison.

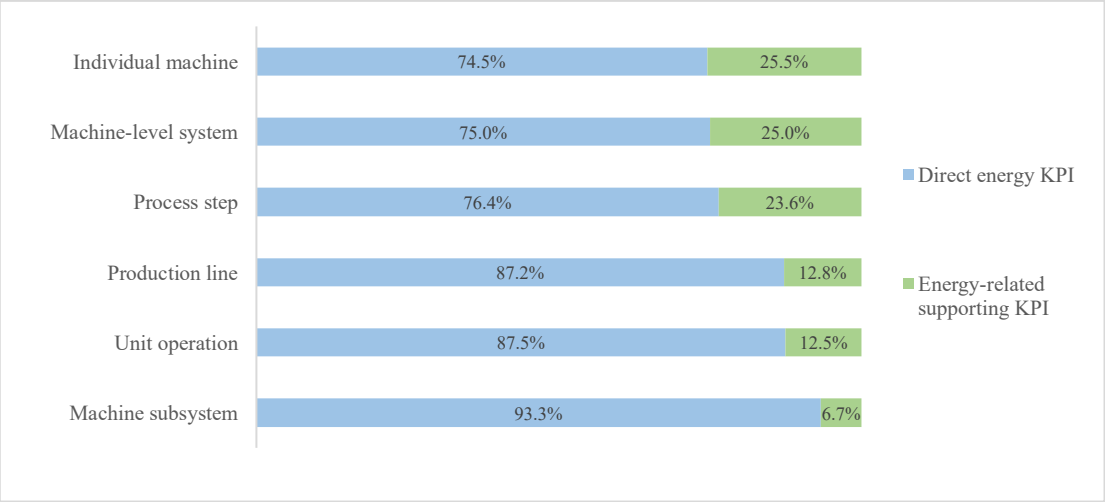

Figure 15. Distribution of direct and supporting energy KPIs across measurement boundaries.

Figure 15 shows that direct energy KPIs dominate across measurement boundaries, but their dominance differs by boundary type. Machine subsystem shows the strongest direct KPI orientation, with 93.3% direct energy KPIs. This indicates that sub machine KPIs are usually linked to measurable or derivable energy quantities, such as component power demand or subsystem energy consumption. Unit operation and production line boundaries also show strong direct KPI dominance, with 87.5% and 87.2% direct KPIs. These boundaries are mainly used to quantify energy use, energy consumption, or energy performance outcomes within a defined operational scope.

Individual machine, machine level system, and process step boundaries show higher supporting KPI shares, with 25.5%, 25.0%, and 23.6%, respectively. Direct KPIs still represent the majority in these boundaries, but supporting indicators are more visible because

operating states, load changes, idle time, process phases, and equipment conditions affect energy performance interpretation. Overall, Figure 15 shows that measurement boundary affects the balance between direct and supporting KPI roles. Boundaries closer to physical energy consuming units support direct measurement, and machine or process related boundaries require supporting indicators for interpretation.

Measurement boundary and manufacturing level are related but distinct dimensions. Figure 16 presents a heatmap of measurement boundaries across manufacturing levels and shows the correspondence between KPI calculation scope and interpretation level.

Boundary \ Level	Machine	Process or Unit operation	Line or Cell
Individual machine	167	3	0
Machine subsystem	41	6	0
Machine-level system	20	0	1
Process step	0	304	5
Production line	0	0	55
Unit operation	0	14	4

Figure 16. Heatmap of measurement boundaries across manufacturing levels.

Figure 16 shows that most KPI entries are concentrated in expected boundary level combinations. Individual machine, machine subsystem, and machine level system boundaries are mainly associated with the machine level. Process step and unit operation boundaries are mainly associated with the process or unit operation level. Production line boundaries are mainly associated with the line or cell level. This confirms the internal consistency of the classification logic because the operational scope used in KPI calculation usually corresponds to the hierarchical level used for interpretation.

The relationship between measurement boundary and manufacturing level is still not fully direct. Some KPIs interpreted at the process or unit operation level use individual machine or machine subsystem boundaries. A smaller number of process step and unit operation boundaries also appear at the line or cell level. This pattern shows that manufacturing level and measurement boundary capture different aspects of KPI meaning. Manufacturing level identifies the KPI position in the production hierarchy. Measurement boundary defines the operational scope included in the calculation. This distinction affects KPI comparability and standard-aligned interpretation. Two KPIs can belong to the same manufacturing level and still differ in meaning if their measurement boundaries differ. A process level KPI calculated

from a process step differs from a process level KPI derived from machine subsystem data. Similarly, a line level KPI based on a full production line boundary differs from one that aggregates selected process step values. Boundary information is therefore needed to avoid misleading comparisons between KPIs with similar names or levels.

Overall, Figures 15 and 16 show that similar KPI labels can have different meanings when measurement boundaries differ. This finding contributes to RQ1 by showing that reported energy KPIs cannot be interpreted only from their names, types, or manufacturing levels. It supports RQ2 by confirming measurement boundary as a separate contextual dimension in the taxonomy. It supports RQ3 because standard mapping requires a clear scope for KPI measurement, calculation, and interpretation.

4.5 Standard Mapping of the Extracted Energy KPIs

This section addresses RQ3 by examining the mapping of extracted energy KPI entries to the selected standards. The analysis first considers ISO 50001 as the primary energy management reference. It then examines the complementary roles of ISO 22400 and ISO 20140 in manufacturing operations performance and environmental manufacturing performance. Before the standards are examined separately, the extracted KPI entries are grouped by standard linkage type. This classification separates explicit standard mentions in the source articles from conceptual mappings assigned by the rule-based procedure of this thesis. It also separates links to the selected thesis standards from links to external standards. Figure 17 presents the distribution of extracted KPI entries by standard linkage type.

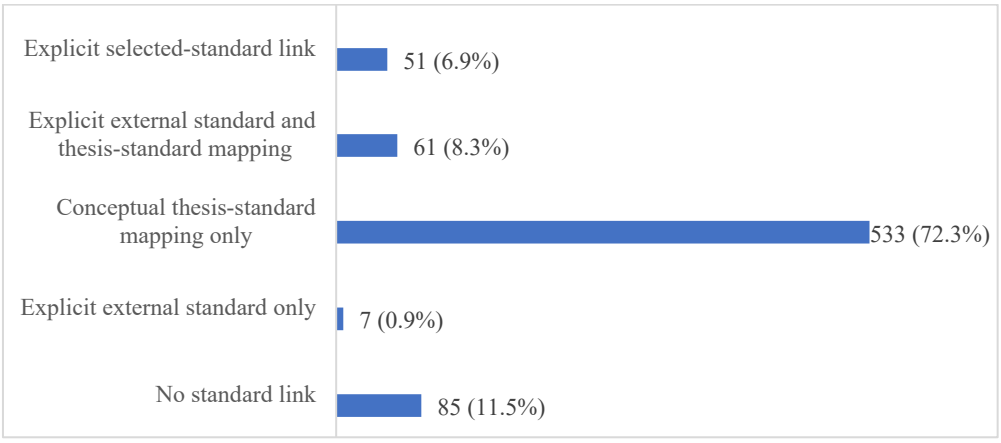

Figure 17. Distribution of extracted KPI entries by standard-linkage type. Percentages are calculated from all KPI entries (n = 737).

Figure 17 shows that standard alignment of the extracted KPI entries mainly results from the thesis mapping procedure, not from explicit standard references in the source articles. The dominant category is conceptual thesis standard mapping only, with 533 KPI entries, or 72.3%. Only 51 entries, or 6.9%, were explicitly linked to one selected thesis standard. This indicates that most studies report energy-related KPIs without direct links to ISO 50001, ISO 22400, or ISO 20140, even when their definition, calculation logic, and intended use support such alignment.

This finding supports the need for a structured standard-aligned framework. If the review relied only on explicit standard mentions, most KPI evidence would remain unclassified from a standard perspective. The 61 entries, or 8.3%, with external standard references and thesis standard mapping also show that reported standards and thesis relevant standards do not always overlap. Standard alignment therefore requires KPI level interpretation. The 85 entries, or 11.5%, with no standard link confirm that some indicators support the framework analytically but do not provide a defensible basis for ISO based mapping. Figure 18 presents the mapped and not mapped proportions for ISO 50001, ISO 22400, and ISO 20140, together with the positive mapping bases assigned to the mapped KPI entries.

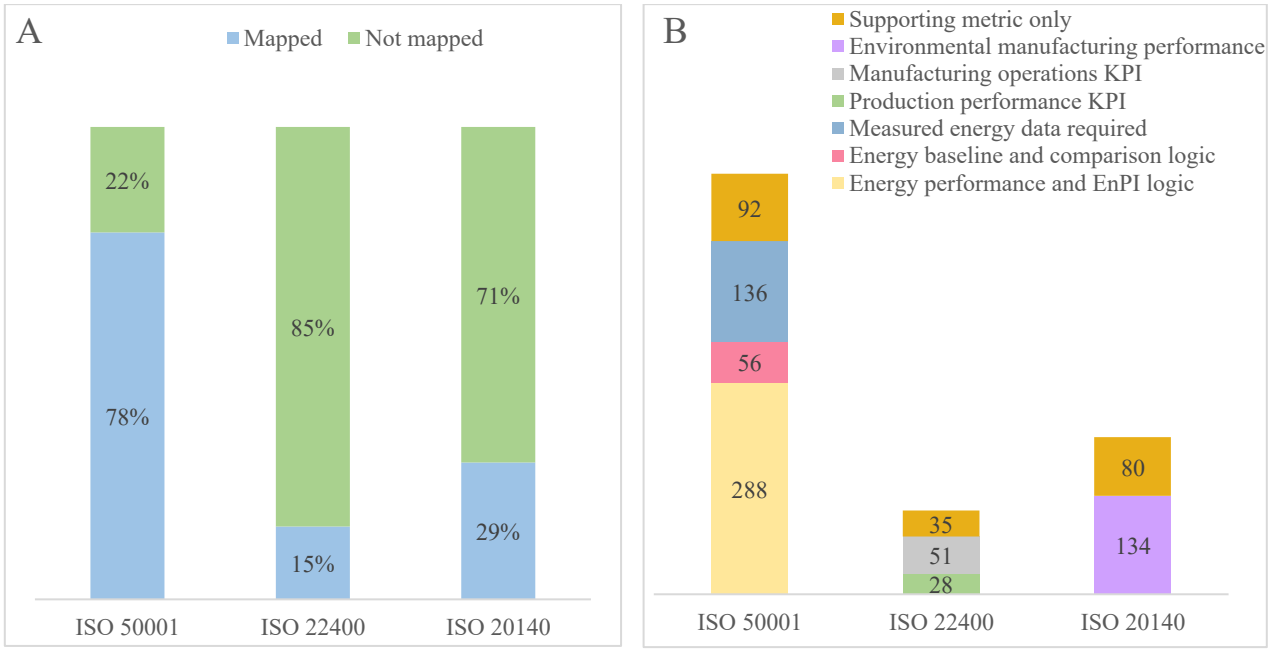

Figure 18. Standard mapping results of the extracted KPIs. Panel A shows the percentage of KPIs mapped and not mapped to each selected standard. Panel B shows the distribution of positive mapping bases among the KPIs mapped to each standard.

Figure 18 shows clear differences in the roles of the three selected standards. ISO 50001 has the widest coverage, with 78% of extracted KPI entries mapped to it. This is expected

because most extracted indicators relate to energy performance, energy use, energy consumption, power demand, energy efficiency, savings, or baseline comparison. ISO 22400 has narrower coverage, with 15% of entries mapped to it. This reflects the stricter mapping rule used in this thesis, since ISO 22400 was assigned only when the KPI represented production performance or manufacturing operations performance. ISO 20140 has intermediate coverage, with 29% of entries mapped to it, mainly where the KPI had an environmental, resource efficiency, carbon, or environmental performance meaning.

The mapping basis results clarify each standard's role. For ISO 50001, Energy performance and EnPI logic is the largest basis with 288 entries, followed by Measured energy data required with 136, Supporting metric only with 92, and Energy baseline and comparison logic with 56. This confirms ISO 50001 as the main structure for energy performance KPIs and measurement support. For ISO 22400, mappings mainly cover Manufacturing operations KPI with 51 entries, Supporting metric only with 35, and Production performance KPI with 28. This standard supports operational interpretation when production behavior, availability, throughput, or scheduling related performance affects energy interpretation. For ISO 20140, mappings concentrate in Environmental manufacturing performance with 134 entries and Supporting metric only with 80. The Life cycle and process environmental assessment basis received no mapped entries. This shows that environmental or resource performance links exist, and explicit life cycle or process environmental assessment logic remains limited. Figure 19 presents the distribution of mapped KPI types across ISO 50001, ISO 22400, and ISO 20140.

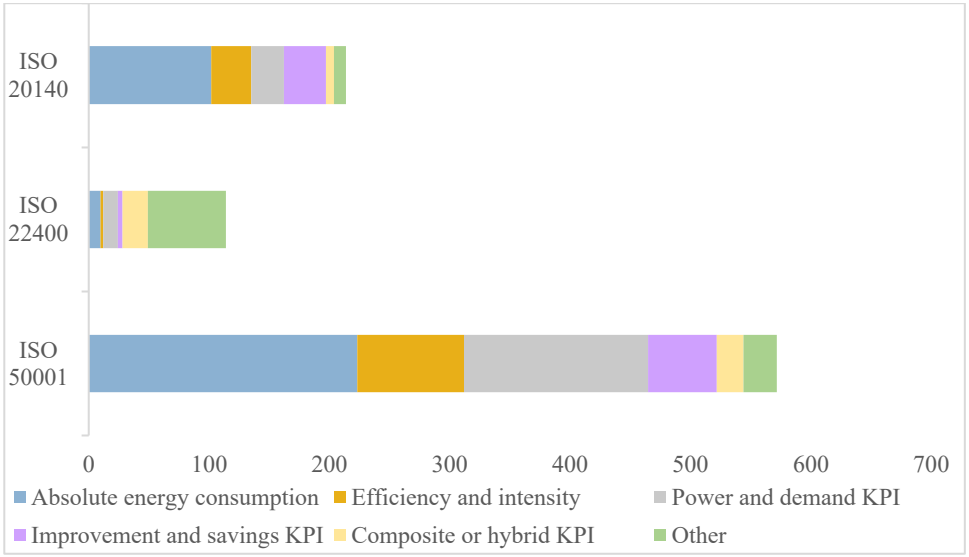

Figure 19. Distribution of mapped KPI types across the selected standards.

Figure 19 shows that ISO 50001 is mainly associated with core energy performance KPI types. The largest mapped group is absolute energy consumption with 223 entries, followed by power and demand KPIs with 153 entries and efficiency and intensity KPIs with 89 entries. This confirms ISO 50001 as the primary reference for KPIs that quantify energy use, energy demand, and energy performance improvement. Improvement and savings KPIs also support its role in baseline comparison and performance improvement assessment.

ISO 22400 shows a different pattern. The number of mapped entries is much smaller, and the mapped KPIs are concentrated mainly in other and composite or hybrid KPI categories. This is consistent with its role in this thesis as a complementary reference for manufacturing operations performance. Only KPIs connected to production behavior, operational performance, OEE related logic, scheduling, availability, or production system interpretation were mapped to ISO 22400. This limited mapping shows that most extracted KPIs are energy oriented, not production performance oriented.

ISO 20140 occupies an intermediate position. Its mapped entries are dominated by absolute energy consumption with 129 entries, followed by power and demand KPIs with 58 entries, efficiency and intensity KPIs with 54 entries, and improvement and savings KPIs with 41 entries. This shows that ISO 20140 is relevant when energy KPIs are connected to environmental manufacturing performance, resource efficiency, carbon related interpretation, or environmental burden. Its role is narrower than ISO 50001 and depends on environmental meaning, not energy measurement alone.

Overall, this section answers RQ3 by showing that the extracted KPI entries can be mapped to the selected standards using layered and rule-based interpretation. ISO 50001 provides the main reference for energy performance, measured energy data, baseline comparison, and EnPI logic. ISO 22400 supports manufacturing operations interpretation. ISO 20140 supports environmental and resource performance interpretation when the KPI has clear environmental meaning. These results show that standard mapping depends on KPI definition, calculation basis, intended use, boundary, and contextual meaning.

4.6 Data Types and Calculation Approaches of the Extracted Energy KPIs

This section examines the data foundations and calculation logic of the extracted energy KPI entries. The aim is to show what types of data were used to derive the KPIs and what

calculation approaches were reported or inferable from the reviewed studies. Figure 20 presents the relationship between data type groups and calculation method groups. Shortened labels are used in the figure for readability. Direct refers to direct measurement, Formula refers to formula-based calculation, Aggregation refers to aggregation or summarization, State/event refers to state- or event-based calculation, Model-based refers to model-based estimation, Baseline refers to comparison or baseline calculation, and Unclear refers to calculation methods that were not clearly reported.

Data type	Direct	Formula	Aggregation	State/event	Model-based	Baseline	Unclear
Aggregated and summarized data	2	13	69	7	2	9	0
Derived and indirect data	3	258	66	52	112	42	5
Recorded operational data	1	0	1	4	0	0	0
Time-resolved measured data	38	14	7	25	6	0	1

Figure 20. Heatmap of data and calculation method groups among extracted KPI entries.

Figure 20 shows that extracted KPI entries are strongly concentrated in derived and indirect data. The largest cell combines derived and indirect data with calculation based on formula, with 258 KPI entries. This indicates that many KPIs are constructed from input variables by equations or calculation logic instead of being measured directly as final KPI values. Derived and indirect data also appear often with model-based estimation, aggregation, calculation based on event or state, and baseline comparison, with 112, 66, 52, and 42 entries, respectively. This pattern shows that energy KPI construction in discrete manufacturing often depends on analytical processing, modelling, and transformation of raw data.

Time-resolved measured data has a different role. It is mainly linked to direct measurement with 38 entries and calculation based on event or state with 25 entries. This reflects the use of power and energy time series for capturing machine behavior, load states, production phases, and operating events. Aggregated and summarized data is mainly linked to aggregation with 69 entries. Recorded operational data appears only in a small number of entries, mainly in calculation based on event or state with 4 entries. The low number of unclear cases also supports extraction reliability, with only 5 derived and indirect entries and 1 time-resolved measured entry having unclear calculation methods.

These results show that KPI extraction cannot be treated as a simple list of reported indicators. Many KPIs need a clear connection between data source, input variables, and calculation method before interpretation or mapping. The dominance of KPI construction based on formulas, models, and derived data supports the use of extraction fields such as required inputs, calculation method, formula availability, data type group, and calculation method group. Figure 21 presents formula availability across KPI types and shows if the calculation basis was explicit, inferable, or weakly specified.

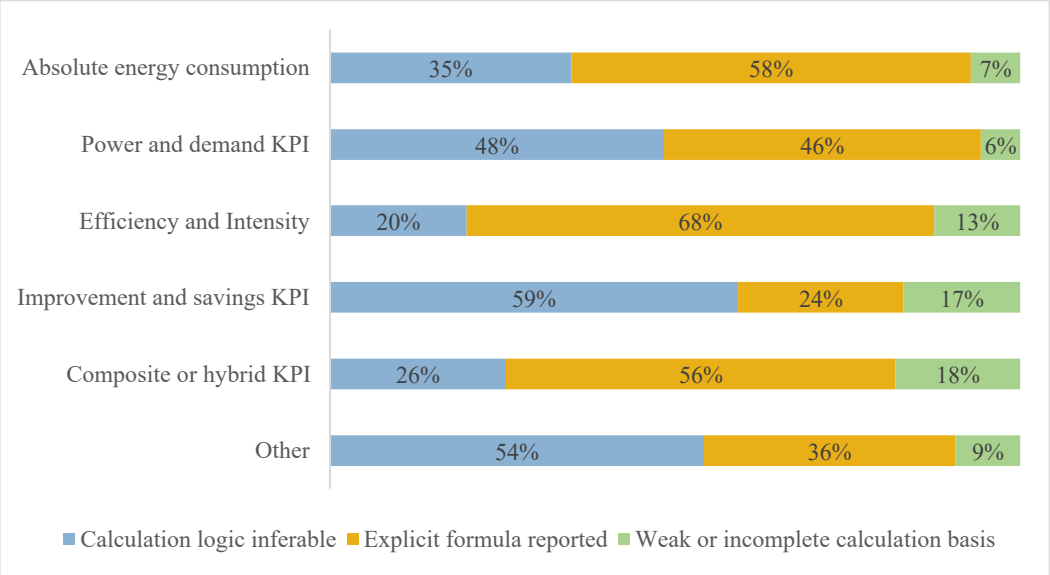

Figure 21. Formula availability across KPI types.

Figure 21 shows that formula availability differs across KPI types. Efficiency and intensity KPIs have the strongest explicit formula basis, with 68% of entries reporting a formula. This is expected because these KPIs usually depend on a defined ratio, such as energy use per output or useful output per energy input. Absolute energy consumption and composite or hybrid KPIs also show high formula reporting, with 58% and 56% explicit formulas. This indicates that many core energy KPIs were sufficiently specified for structured extraction.

The pattern differs for improvement and savings KPIs, where 59% of entries rely on inferable calculation logic and only 24% report an explicit formula. These indicators are often described by comparison logic, reduction, savings, or before and after assessment instead of a closed form equation. Power and demand KPIs are almost evenly divided between inferable logic and explicit formula reporting. This reflects their mixed nature, since some are directly measured from power or load profiles, while others are calculated as averages, peaks, demand values, or state-based summaries. Weak or incomplete calculation

basis is limited overall, but it is most visible in composite or hybrid KPIs and improvement and savings KPIs, with 18% and 17%, respectively. These KPI types often combine several variables, assumptions, or contextual conditions, so incomplete calculation basis makes comparison, operationalization, and standard mapping harder.

Overall, Figures 20 and 21 address the part of RQ1 on KPI definition and computation. The reviewed KPIs are mainly built from derived data, formulas, models, aggregation, and state-based interpretation, and formula availability differs across KPI types. These findings show that KPI usability depends on data basis, required inputs, calculation method, and formula transparency. They support using these elements as classification fields in the framework.

4.7 Framework Roles of the Extracted KPIs

Framework role was used to clarify the function of each extracted KPI in the proposed classification framework. Section 4.6 examined the technical characteristics of the KPIs, including data type and calculation approach. This section focuses on their functional position in the framework. The extracted KPIs were divided into three groups: measurement enabling KPIs, decision-layer KPIs, and supporting KPIs. This distinction separates KPIs that directly support energy performance assessment from indicators that provide contextual, auxiliary, or interpretive information. Figure 22 presents the distribution of these framework roles across three energy KPI status categories: direct energy KPI, energy-related supporting KPI, and not an energy KPI. This comparison shows the type of evidence included in each framework role.

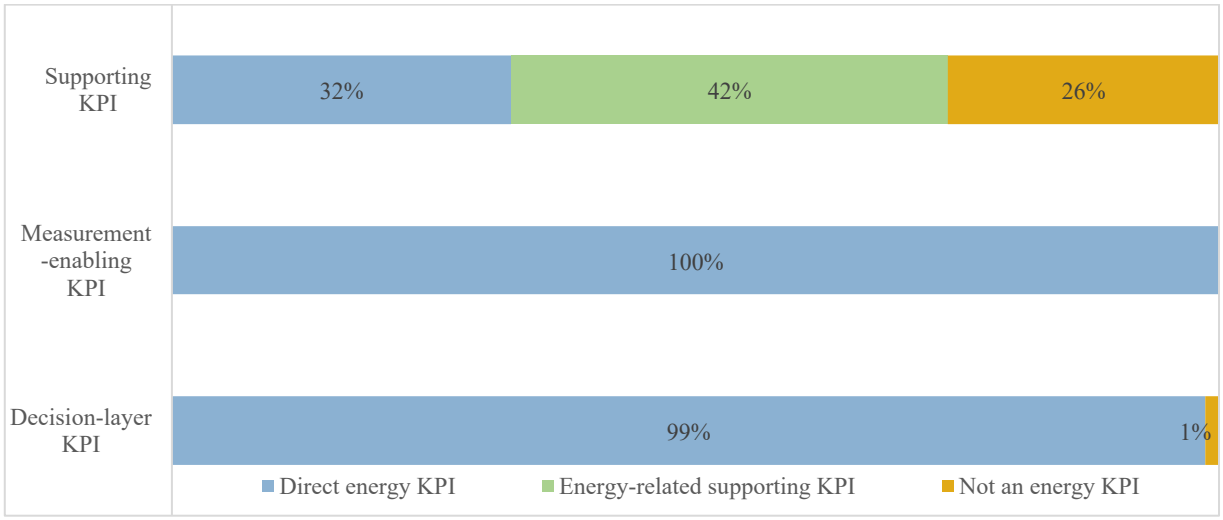

Figure 22. Distribution of framework roles by energy KPI status.

Figure 22 shows a clear relationship between framework role and energy KPI status. All measurement enabling KPIs are direct energy KPIs, which confirms their role as the measurable basis of the framework. These indicators represent observable or computable energy quantities, such as power demand and energy consumption, and provide evidence for KPI calculation, traceability, and ISO 50001 alignment. Decision-layer KPIs are also mainly direct energy KPIs. About 99% of this group belongs to direct energy indicators, which shows that most decision-layer indicators in the reviewed studies are grounded in measurable energy performance. This supports the framework logic because decision-layer KPIs should remain traceable to measured energy data and avoid broad sustainability claims.

A small exception appears in the decision-layer group. About 1%, equal to 4 KPI entries, are classified as Not an energy KPI. These entries are carbon emission, machine tool carbon emission, workpiece carbon emission, and workshop carbon emission. They are excluded from the strict energy KPI scope because they do not measure energy performance directly. They combine energy consumption with other information, including material use, tool use data, production states, logistics, and workshop context. They still have a decision-layer role because they support low carbon evaluation, prediction, and control. In the proposed framework, these indicators should be treated as higher level environmental decision outputs, not as core energy KPIs.

The supporting KPI group has the most mixed structure. It includes direct energy KPIs, energy-related supporting KPIs, and non-energy KPIs. This shows that supporting indicators mainly provide context for energy performance interpretation. They may explain operating conditions, production states, model quality, or process behavior. They should not automatically be treated as EnPIs.

Overall, Figure 22 supports the framework development aim of this thesis by showing that extracted KPIs can be organized by operational role. This result mainly addresses RQ2 by distinguishing measurement enabling, supporting, and decision-layer functions. It also contributes to RQ1 by linking these roles to energy KPI status. This confirms that the proposed taxonomy separates measurable energy indicators, contextual indicators, and decision-layer indicators.

5 KPI Taxonomy for Energy Performance in Discrete Manufacturing

Chapter 5 develops the KPI taxonomy from the extracted KPI evidence in Chapter 4. It structures KPI types for energy performance interpretation in discrete manufacturing. The main text does not repeat the full 737 KPI entries. An excerpt from KPI-level traceability table for taxonomy assignment and framework support is provided separately (Appendix 6).

5.1 Taxonomy Development and Classification Criteria

Chapter 4 showed that extracted KPI entries differed in manufacturing level, measurement boundary, data basis, calculation method, and formula availability. This variation shows that KPI names alone are insufficient for interpretation. Chapter 5 consolidates the evidence into taxonomy groups using analytical meaning, calculation logic, operational context, and standard relevance.

The taxonomy was developed at individual KPI entry level because one study could report several KPIs with different meanings, calculation methods, boundaries, and framework roles. Each KPI entry was treated as a separate classification unit. The full extraction table included 737 KPI entries. The taxonomy reduced these entries into meaningful KPI types while preserving their operational interpretation. Chapter 5 uses the detailed KPI type classification because it defines the final KPI categories used in this thesis.

The classification criteria preserved each KPI's analytical form and operational meaning. Energy performance indicators operate at different levels, and their interpretation depends on boundary, data basis, baseline logic, and intended user level. The taxonomy therefore used KPI type, boundary, manufacturing level, calculation logic, and data availability as classification criteria. This structure made complex energy evidence easier to compare and communicate across manufacturing contexts and detail levels. It also addressed relevant variables and boundary level because one general energy efficiency indicator is insufficient for all manufacturing cases(Benedetti et al. 2017; Kanchiralla et al. 2020).

In this thesis, KPI entries were classified by measured object, calculation basis, normalization logic, boundary, manufacturing level, and role in energy performance interpretation. Standards added the interpretive layer. ISO 50001 was the main reference for direct energy performance KPIs because it defines energy performance in relation to energy efficiency, energy use, and energy consumption. It links EnPIs with baselines, relevant variables, and normalization (ISO 50001 2018). ISO 22400 supported manufacturing operations interpretation because it defines KPI content and context with scope, formula, unit, timing, usage, audience, and production methodology (ISO 22400-1 2014). ISO 20140 supported environmental manufacturing KPIs because it addresses environmental performance in manufacturing systems, including energy efficiency and other environmental factors (ISO 20140-1 2019).

Based on this logic, the taxonomy distinguishes six KPI groups. These groups are absolute energy consumption KPIs, power and demand KPIs, normalized specific and efficiency KPIs, improvement savings and energy loss KPIs, state based and time based KPIs, and composite hybrid and context specific KPIs. Related original KPI types were consolidated under one group if they shared the same analytical logic. Specific and intensity KPIs, plus energy efficiency ratios, were grouped under normalized specific and efficiency KPIs. State based and time based KPIs were grouped together because they explain energy behavior by operating states, process phases, and time intervals. Context specific and weakly specified forms were placed under the composite hybrid and context specific group. Table 13 presents taxonomy groups and classification logic for the extracted KPI entries.

Table 13. Taxonomy groups and classification logic for the extracted KPI entries.

Taxonomy group	Classification logic	Typical examples
Absolute energy consumption KPIs	Energy amount over a defined boundary without normalization	Total energy consumption, idle energy, cutting energy
Power and demand KPIs	Power level, load profile, or demand behavior over time	Average power, peak power, power demand
Normalized, specific, and efficiency-based KPIs	Energy use related to output, useful work, production quantity, or efficiency relation	Specific energy consumption, energy per part, energy efficiency
Improvement, savings, and energy-loss KPIs	Reduction, deviation, avoidable consumption, or comparison against a reference condition	Energy saving, energy loss, reduction rate
State-based and time-based KPIs	Energy or power linked to machine states, process phases, cycles, events, or time intervals	Standby energy, cycle energy, interval energy
Composite, hybrid, and context-specific KPIs	Combined, model-based, weakly specified, or context-dependent KPI forms	Predicted energy index, carbon-related indicators, model-based KPI

These groups address RQ2 by structuring KPI entries by analytical meaning, computation logic, operational context, and standard relevance. They also support standard-aligned classification and practical interpretation in Chapter 6.

5.2 Absolute Energy Consumption KPIs

Section 3.7.1 linked KPI type classification to Kanchiralla et al.'s (2020) EnPI categories, including absolute energy use, ratio indicators, statistical models, and simulation indicators. Absolute energy consumption KPIs form the first taxonomy group because they give the most direct expression of energy use. This logic aligns with ISO 50001 because energy consumption means the quantity of energy applied, and energy performance relates to energy efficiency, energy use, and energy consumption (ISO 50001 2018). These KPIs need a clear operational boundary, reliable data, and a defined level of energy performance control to become meaningful (Benedetti et al. 2017). Table 14 summarizes this group by boundary, framework role, calculation method, and input requirement.

Table 14. Boundary-based synthesis of absolute energy consumption KPIs.

Boundary	KPI entries	Dominant role	Dominant calculation logic	Dominant input requirement	Main interpretation
Process step	106	Decision-layer KPI	Formula-based; state and event-based	Energy plus time or state	Operation-level energy characterization
Individual machine	53	Decision-layer KPI	Aggregation; formula-based; state and event-based	Energy plus time or state	Direct machine-level energy evidence
Multi-machine system	31	Decision-layer KPI	Aggregation; formula-based	Energy plus time or state	System-level decision support
Production line	11	Decision-layer KPI	Formula-based; aggregation; baseline calculation	Energy plus time or state	Line-level performance and loss analysis
Machine subsystem	10	Supporting and measurement-enabling KPI	Aggregation; formula-based; model-based	Energy plus time or state; process parameters	Diagnostic subsystem energy transparency
Multi-level	7	Decision-layer KPI	Aggregation	Energy plus time or state	Part or route-level energy assessment
Unit operation	4	Decision-layer KPI	Aggregation; formula-based	Mixed inputs	Operation or subsystem baseline assessment
Machine-level system	1	Measurement-enabling KPI	State and event-based	Energy plus time or state	State-based machine energy decomposition

Table 14 shows that absolute energy consumption KPIs express energy amounts with different analytical roles. The largest group appears at process step level, linking energy use to a defined operation, event, and working step. This explains the frequent use of formula calculation and state or event calculation. At individual machine level, this group provides direct machine energy evidence. Its meaning depends on operating state, monitoring period, and production context. Meaningful interpretation requires temporal or state information.

At subsystem level, this group shifts from energy accounting to diagnostic transparency. Spindle, auxiliary equipment, and component energy consumption show internal energy use inside the machine or technical system, requiring separate measurement channels, component signals, or model estimation. At line, cell, and multi machine system boundaries, these KPIs support scheduling, process planning, scenario comparison, and baseline analysis. Their main limitation is lower diagnostic resolution because aggregated values can hide the responsible machine, operation, or state.

The extracted KPIs show that absolute energy consumption varies by case. In P053, E_{total}(Mi) sums machining and waiting energy across all phases of Machine Mi and functions as machine level energy accounting for energy aware rescheduling and machine energy comparison (Wang et al. 2018). In P099, E_{ws}, combines standby, air cutting, and effective cutting energy. It shifts interpretation to process step energy characterization because energy is assigned to a specific machining working step (Cheng et al. 2022). In P050, ΔI_{C5} expresses slowdown related energy loss in kWh and provides loss and improvement evidence by quantifying non value adding energy caused by increased cycle time (Nota et al. 2020).

Absolute energy consumption KPIs provide the measurement foundation for energy performance interpretation. Their meaning depends on boundary, calculation logic, inputs, and intended use. Efficiency claims require additional context.

5.3 Power and Demand KPIs

Section 5.2 analyzed energy amount by boundary. Section 5.3 shifts the focus to power level, load demand, and energy behavior over time. This group focuses on power behavior instead of accumulated energy.

$P_{cooling}$ in P081represents cooling system power demand during the active cooling state and reports 268 W. If the state lasts for time t, the value can be converted into consumed energy. $P_{cooling}$ identifies state specific auxiliary load inside the machine cycle and supports average cycle power and energy modelling (Xie et al. 2016). This example shows that power and demand KPIs need separate analytical logic from absolute energy consumption KPIs. The focus is the operating power state and its effect on load profile over time. This section uses monitoring and measurement logic, and examines these KPIs as measured signals, model-based power estimates, state related demand values, and decision support inputs. Table 15 summarizes this logic by role, calculation method, and input requirement.

Table 15. Synthesis of monitoring and measurement roles for power and demand KPIs.

Analytical role	KPI entries	Dominant calculation logic	Dominant input requirement	Interpretation in this taxonomy
Measurement-enabling power signals	82 entries	Direct measurement; model-based estimation; aggregation	Energy or power only; energy plus process parameters; energy plus time or state	Makes power behavior observable for monitoring, load profiling, state recognition, and later energy calculation
Supporting power interpretation	48 entries	Aggregation; model-based estimation; state and event-based calculation	Energy plus process parameters; energy plus time or state	Explains load behavior by connecting power values to operating states, machine conditions, or process context
Decision-layer power use	27 entries	Aggregation; state and event-based calculation; model-based estimation	Energy plus process parameters; energy plus time or state	Supports scheduling, control, demand reduction, or efficiency assessment when power values are linked to decision variables

Table 15 shows that power and demand KPIs mainly act as visibility indicators. The cross tabulation supports this result because 82 of 157 entries were measurement enabling KPIs. Their main role is to make power behavior observable before further energy performance interpretation. They support load monitoring, state recognition, demand profiling, and later energy calculation. P_t in P237 shows this role. Active power is read from the power meter and used to identify machine states, count parts, detect stops, and calculate per part energy. This KPI makes machine behavior visible from the power profile (Da Costa et al. 2024).

The calculation logic shows that this group extends beyond direct measurement. Model-based estimation was the largest calculation group, with 51 entries. This means that power demand is often estimated from process conditions. P_{cut} in P152 shows this logic. It is calculated from process specific cutting parameters and fitted coefficients and supports

cutting power estimation and whole machine energy prediction (Shen et al. 2018). The input pattern confirms the same interpretation. The largest group was energy plus process parameters with 74 entries, followed by energy plus time or state with 43 entries, and energy or power only with 37 entries. This shows that power and demand KPIs usually need cutting parameters, operating states, machine conditions, or time windows. An isolated power value can show load, although its cause and operational meaning need additional context.

P_{tot} in P215 is a special case. It combines total electric power, equivalent pneumatic power, and thermal equivalent power. Its interpretation goes beyond electrical load monitoring because it represents total supplied machine power for energetic process efficiency assessment. This shows that some power and demand KPIs move from monitoring to decision-layer interpretation after combining several energy carriers or resource related power terms (Hacksteiner et al. 2017). Power and demand KPIs form the monitoring layer of the taxonomy. They make load behavior visible over time and need process parameters, operating states, calculation logic, and intended use for energy performance interpretation.

5.4 Normalized and Efficiency-Based KPIs

Section 5.4 focuses on normalized specific and efficiency KPIs. These KPIs relate energy use to a reference variable such as output, material removal, production quantity, time, state, process parameters, or resource information. SEC in P065 shows this logic. It is calculated as cutting power divided by material removal rate and reported in J/mm³. It shows the energy required to remove one unit of material and supports comparison of machining energy intensity under similar parameter settings (Yang et al. 2023)

Normalized KPIs improve comparability by expressing energy per part, block, removed material volume, or production output. This moves interpretation closer to energy performance than absolute consumption alone. The comparison is reliable only with a comparable denominator. Product complexity can make kWh per part misleading because the denominator may miss production effort. Table 16 reports KPI entry counts by input requirement group and KPI type.

Table 16. Normalization-based synthesis of specific and efficiency-based KPIs.

Normalization logic	KPI entries	Dominant calculation logic	Main interpretation	Main limitation
Energy plus production output	59: 46 S; 13 E	Formula-based calculation	Compares energy use against produced parts, product units, material removal, or production quantity	Reliable only when outputs are comparable
Energy plus time or state	10: 0 S; 10 E	Formula-based calculation	Relates energy performance to active time, operating state, cycle, or period	Time or state does not always represent useful output
Energy plus process parameters	11: 5 S; 6 E	Formula-based calculation	Connects energy performance to machining or process conditions	Sensitive to parameter selection and model assumptions
Energy plus resource or environmental data	6: 2 S; 4 E	Formula-based calculation	Extends energy interpretation to resource or environmental terms	Comparability depends on consistent resource boundaries
Non-energy contextual input	7: 5 S; 2 E	Formula-based or weakly specified logic	Uses contextual variables to interpret energy-related performance	Risk of unclear energy-performance meaning
Energy or power only	3: 1 S; 2 E	Formula-based calculation	Uses direct energy or power values in a ratio or normalized expression	Weak normalization if no output reference is included

Note: S = specific and intensity-based energy KPI; E = energy efficiency ratio.

Table 16 shows that this KPI group mainly serves decision-layer use. In total, 79 of 96 entries were classified as decision-layer KPIs. The pattern is strongest for specific and intensity KPIs, with 50 of 59 entries in the decision-layer. These KPIs mainly support performance comparison and decision support. The dominant normalization basis is production output, with 59 of 96 entries requiring energy plus production output. In P076, total line energy use per product is reported as 75.258 kWh per block and supports line level benchmarking. Its interpretation is reliable for similar products and line conditions (ElMaraghy et al. 2017). Formula calculation is dominant, with 73 of 96 entries. This shows that normalized and efficiency KPIs are usually built from a defined relation between energy input and a reference variable. In P109, $\eta_{machine}$ measures cutting energy utilization as cutting energy divided by total machine tool energy, and can indicate standby or air cutting losses (Chen et al. 2018a).

Efficiency ratios are more diverse than specific KPIs. They appear across production output, time or state, process parameters, resource data, and contextual inputs. In P154, PAEE, part energy efficiency, is calculated as cutting state energy divided by the sum of cutting, tool, buffer, and conveying energy related to the part. This KPI compares useful cutting energy with the wider energy burden of producing the part and requires consistent decomposition

of part related energy terms (Zhang et al. 2017). Taken together, Normalized and efficiency KPIs improve comparability and require comparable denominators and process conditions for reliable interpretation.

5.5 Improvement, Savings, and Loss KPIs

Improvement, savings, and loss KPIs compare energy performance with a reference condition, such as a previous machine state, process state, conventional strategy, baseline model, expected value, or ideal operation. Their meaning comes from reduction, saving, loss, or deviation against that comparison point. In P148, energy saving rate compares adaptive control energy use with conventional machining energy use and reports percentage reduction (Won et al. 2023). Table 17 summarizes this group by reference logic, framework role, and calculation method.

Table 17. Reference-based synthesis of improvement, savings, and loss KPIs

Reference or comparison logic	KPI entries	Dominant framework role	Dominant calculation logic	Main interpretation	Main limitation
Baseline or reference comparison	32	Decision-layer KPI	Comparison or baseline calculation	Measures saving, reduction, or improvement against a defined reference condition	Reliability depends on the validity of the baseline or reference case
Formula-based saving or loss calculation	20	Decision-layer KPI	Formula-based calculation	Quantifies saving, reduction, or loss through explicit equations	Weak if the formula does not clearly define the reference condition
Model-based improvement estimation	10	Decision-layer KPI	Model-based estimation	Estimates improvement under optimized or simulated conditions	Depends on model assumptions and scenario design
Aggregated improvement summary	7	Decision-layer KPI	Aggregation or summarization	Summarizes energy improvement or saving across a period, process, or system	May hide the source of saving or loss
State or event-based loss logic	2	Decision-layer KPI	State or event-based calculation	Links loss or saving to specific operating states or events	Requires reliable state or event identification

Table 17 shows that improvement, savings, and loss KPIs strongly depend on reference logic. Comparison or baseline calculation is the largest group, with 32 of 71 entries. This means that most KPIs in this category become meaningful after actual performance is

compared with a defined reference condition. P118 illustrates this pattern. Electricity saving percentage compares electricity saving with baseline predicted electricity consumption, and the study reports an average saving of 4.3%. The KPI measures the effect of energy management implementation because a baseline electricity value is available (Cabello Eras et al. 2019). This group mainly supports decision-layer use, with 56 of 71 entries classified as decision-layer KPIs.

Savings and losses usually evaluate the effect of a change, control method, or operational decision. P202 shows this logic. Energy reduction achieved by genetic algorithm routing is calculated by comparing cumulative energy under genetic algorithm routing with the baseline machine load balancing method routing strategy. The reported saving of about 2000 energy units shows better performance than the reference routing strategy (Ladosz et al. 2018). Loss oriented KPIs use the same reference logic, often between productive and non-productive operation. In P300, idle running share of machine electricity consumption is calculated as idle or waiting state electricity divided by total machine electricity consumption. The reported 33 percent idle running share identifies electricity use outside productive operation. This KPI turns monitored energy use into loss evidence by separating idle or waiting energy from total machine electricity use (Cosgrove et al. 2016).

The calculation pattern also shows a quality issue. Comparison or baseline calculation dominates the group, while entries based on formulas or models and aggregated entries are also present. KPI reliability depends on the reference structure behind the calculation. A weak baseline, unrealistic optimized scenario, or unclear state separation can produce a saving or loss value with weak analytical reliability. Improvement, savings, and loss KPIs provide the strongest link between KPI extraction and improvement decisions. They translate energy data into evidence of reduction, avoidable waste, or operational improvement. Their main limitation is reference dependence. A saving or loss value is defensible only with a clearly defined baseline, comparison case, or loss attribution.

5.6 State-Based and Time-Based KPIs

State based and time based KPIs add timing and operating condition detail to the absolute energy consumption KPIs discussed in Section 5.2. Absolute energy consumption KPIs show total energy within a defined boundary. State based and time based KPIs extend this

evidence by linking energy or power values to machine states, process states, events, and time windows. This section uses state and time segmentation as the main analytical logic. Table 18 summarizes the segmentation logic of these KPI entries by KPI type, framework role, calculation method group, input requirement group, and boundary distribution.

Table 18. State and time segmentation synthesis of state-based and time-based KPIs

Segmentation logic	KPI entries	Dominant framework role	Dominant calculation logic	Main interpretation	Main limitation
Time-window segmentation	33 time-based KPIs	Supporting KPI	Aggregation or formula-based calculation	Links energy or power to process time, cycle time, delay, interval, or monitoring period	Requires clear time boundaries
State-based segmentation	6 state-based KPIs	Supporting KPI	State or event-based calculation	Links energy or power to operating states such as processing, blockage, starvation, sleep, failure, or abnormal conditions	Requires reliable state labels
Process-step timing	22 entries at process-step boundary	Supporting KPI	Time-based or state-based calculation	Explains energy behavior within specific process steps or operations	Depends on correct process segmentation
Energy plus time or state input	34 entries	Supporting KPI	Mixed, mainly aggregation, formula-based, or state-based	Shows that most KPIs require energy or power values linked to time, duration, state, or event data	Weak if timestamps or state information are missing
Interpretation support	39 entries	Supporting KPI	Mixed calculation logic	Provides context for interpreting energy use, anomaly detection, and later improvement analysis	Usually does not act as final performance evidence alone

Table 18 shows that state based and time based KPIs mainly function as supporting indicators. All 39 entries in this group were supporting KPIs. Their role is to make energy or power data interpretable by linking values to states, events, time windows, and reference patterns. The strongest pattern is time segmentation, with 33 time-based entries and 6 state based entries. This shows stronger use of time segmentation than explicit state classification in the reviewed literature. The KPI time delay between energy patterns in P086 illustrates this logic. It is calculated as the lag that maximizes cross correlation between a measured

energy signal and a standard energy signal. It supports energy pattern alignment before deviation analysis and anomaly classification (Li & Cai 2018).

The input pattern confirms this interpretation. In total, 34 of 39 entries require energy plus time or state. Energy or power values alone are insufficient for this group. The KPI becomes meaningful after the value is linked to duration, timestamp, event boundary, operating state, or reference pattern. The no energy consumption condition in P086 shows this logic. It is detected after the monitored energy pattern shows no energy consumption during expected operation. In this context, absence of energy use signals machine breakdown and supports abnormal condition detection (Li & Cai 2018).

The boundary distribution concentrates at process step level, with 22 entries. At this level, timing and operating condition give more insight than total energy alone. Machine state time distribution in P070 adds the state-based layer by dividing machine time across processing, blockage, starvation, failure, and sleep states. It shows energy saving control changes because blockage or starvation time can shift into sleep time and change the energy profile (Wang et al. 2019b). The calculation pattern shows that this KPI group has no single formula type. It includes aggregation, formula calculation, model estimation, and state or event calculation. The common feature is segmentation. State based and time based KPIs become useful after energy or power values are assigned to valid states, events, delays, cycles, or time windows. Their value depends on reliable time boundaries, state labels, event definitions, and reference patterns.

5.7 Composite, Hybrid, and Other Context Specific KPIs

Composite hybrid and context specific KPIs cover entries outside the simpler KPI groups. They combine performance components, model logic, context variables, or indirect support for energy performance interpretation. Overall Equipment Effectiveness (OEE) from P001 shows a composite form because it combines availability, performance, and quality, and helps interpret energy use against effective production and losses (Dudzik et al. 2026). Hybrid KPIs use mixed data sources or methods. T(k) from P061 shows a hybrid form because it links tool aging and model coefficients to predicted energy behavior (Liang et al. 2018). Other entries include model error, confidence bounds, and carbon related measures.

Table 19 presents the analytical patterns, dominant framework roles, classification evidence, main interpretations, and limitations for this group.

Table 19. Interpretability and classification synthesis of composite, hybrid, and context-specific KPIs

Analytical pattern	KPI entries	Dominant framework role	Main classification evidence	Main interpretation	Main limitation
Composite and hybrid indicators	94	Supporting KPI	88 supporting; 6 decision-layer	Combine several components or rely on model-based logic to support energy-performance interpretation	Often indirect and less suitable as standalone EnPIs
Other context-specific indicators	57	Supporting KPI	57 supporting; 0 decision-layer	Capture article-specific, contextual, environmental, cost, or model-validity information	Limited standardizatio n and weak comparability across studies
Non-energy contextual dependence	96	Supporting KPI	49 composite/hybrid; 47 other	Energy interpretation depends strongly on operational, quality, model, or contextual variables	High risk of unclear energy-performance meaning
Energy-related supporting role	92	Supporting KPI	77 composite/hybrid; 15 other	Supports energy interpretation without directly measuring energy performance	Needs clear explanation of its link to energy use or EnPI logic
Non-energy or weakly energy-related indicators	51	Supporting KPI	11 composite/hybrid; 40 other	Represents contextual or methodological information rather than energy performance itself	Should not be treated as direct energy KPIs
Decision-layer exceptions	6	Decision-layer KPI	All within composite/hybrid group	Used directly for decision support when the composite or hybrid indicator is tied to energy improvement, efficiency, or operational control	Requires careful justification of the decision role

Table 19 shows that composite hybrid and context specific KPIs are mainly interpretive. In total, 145 of 151 entries were supporting KPIs, and 6 entries were decision-layer KPIs. This confirms that most indicators in this group explain, validate, or contextualize energy behavior instead of measuring energy performance directly. The pattern is strongest in the composite and hybrid subgroup, with 88 of 94 entries classified as supporting KPIs. R^2 from P082 illustrates this role. It assesses the reliability of the regression baseline model used for energy saving estimation and verification. This makes it useful for measurement and verification logic, and weak as a direct energy KPI (Oses et al. 2016).

Table 19 also shows strong dependence on non-energy contextual input. In total, 96 entries follow this pattern, including 49 composite or hybrid entries and 47 other context specific entries. Many KPIs in this group need contextual data beyond energy data alone. P066 shows this point. Tool flank wear value (VB) supports energy interpretation because tool wear changes cutting conditions, cutting power, and energy behavior. It remains a supporting contextual variable outside direct EnPI logic (Wu et al. 2024). The “non-energy or weakly energy-related” pattern includes 51 entries, with 40 entries in the “other” category. This category prevents model quality, machine condition, material behavior, or contextual state from being treated as direct energy performance evidence. It strengthens the taxonomy by separating supporting context from direct energy KPI logic.

Resource related entries add a resource dimension to this interpretation. Compressed air consumption prediction in P222 extends the framework beyond direct electrical energy measurement. The KPI uses a hybrid virtual metering approach based on machine Light Emitting Diode (LED) state signals or internal machine signals. It supports resource flow transparency close to real time for machines without direct Programmable Logic Controller (PLC) data connection. Its interpretation depends on the virtual metering model and suitable machine state signals, so it supports resource transparency with weaker standardization than directly measured electrical energy consumption (Sossenheimer et al. 2021).

Decision-layer exceptions are limited. Only 6 entries were classified as decision-layer KPIs, all within the composite or hybrid subgroup. OEE Plus from P237 illustrates this exception. It extends conventional OEE by combining availability, performance, quality, and an energy indicator. OEE Plus is expressed as $A \times P \times Q \times EI$ and supports real time assessment of efficiency and sustainability in legacy machine tools. This example shows that a complex KPI becomes decision relevant if its combined structure directly supports energy performance assessment or operational decisions (Da Costa et al. 2024).

Composite hybrid and context specific KPIs extend energy performance analysis beyond direct energy measurement by linking energy behavior to operational effectiveness, model validity, resource use, tool condition, and sustainability interpretation. Their main role is supporting interpretation, so framework use requires clear justification of calculation logic, boundary, input requirements, and link to energy performance decisions.

5.8 From KPI Taxonomy to Framework Role

The taxonomy defines the analytical meaning of each KPI group. Table 20 links these groups with the framework roles used in Chapter 6.

Table 20. Translation rules from KPI taxonomy to framework role.

Taxonomy group	Main analytical logic from Chapter 5	Likely framework role	Decision rule
Absolute energy consumption KPIs	Boundary-based energy amount	Measurement-enabling or decision-layer	Measurement-enabling when used as energy evidence; decision-layer when used for assessment, comparison, scheduling, or loss analysis
Power and demand KPIs	Monitoring and measurement logic	Mostly measurement-enabling	Measurement-enabling when used as load/power evidence; decision-layer when linked to control, peak reduction, or efficiency decisions
Normalized, specific, and efficiency-based KPIs	Normalization logic	Mostly decision-layer	Decision-layer when energy is related to output, useful work, production quantity, or efficiency relation
Improvement, savings, and loss KPIs	Reference and baseline logic	Mostly decision-layer	Decision-layer when the KPI compares actual performance with baseline, reference, or expected condition
State-based and time-based KPIs	State and time segmentation logic	Mostly supporting	Supporting when the KPI explains when or under which condition energy use occurs
Composite, hybrid, and context-specific KPIs	Interpretability and classification logic	Mostly supporting, with exceptions	Supporting when the KPI validates, explains, or contextualizes energy performance; decision-layer only when the link to energy decision is explicit

KPI type alone is insufficient for framework role assignment. Role assignment depends on boundary, inputs, calculation logic, and intended use. Measurement enabling KPIs provide direct energy evidence. Decision-layer KPIs support comparison, baseline assessment, improvement, optimization, and performance judgement. Supporting KPIs explain operating context, model validity, resource conditions, state behavior, and interpretation limits.

Section 4.7 supports this role structure, and Section 4.5 gives the standard basis. ISO 50001 supports the energy performance layer via EnPI logic, measured energy data, and baseline comparison (ISO 50001 2018). ISO 22400 supports manufacturing operations interpretation, and ISO 20140 supports environmental interpretation for KPIs with clear environmental or resource performance meaning (ISO 20140-1 2019; ISO 22400-1 2014).

6 Proposed Framework for Energy KPI Structuring

Chapter 6 develops the decision framework from the Chapter 5 classification results. It explains the framework logic and applies it to the Hydroforming 8 dataset to select usable KPI candidates from available operational data.

6.1 Motivation for the Framework

The earlier chapters positioned this study within fragmented manufacturing energy efficiency literature and defined the indicator concepts used in the thesis (Ibn Batouta et al. 2023). Chapter 5 classified the extracted KPI entries by analytical type. This classification supports comparison across papers, yet Section 5.8 shows a further methodological need. KPI type alone was insufficient for assigning framework role. Indicator role changes with boundary, manufacturing level, input variables, calculation logic, baseline relation, and intended use. The framework addresses the gap between classification and application by linking each KPI entry to the conditions that make it meaningful for a specific operational dataset. This follows energy performance logic, where EnPI interpretation depends on aggregation level, decision level, boundary, relevant variables, and monitored context (Benedetti et al. 2017; Kanchiralla et al. 2020).

The selected form is a decision framework because the task is a selection. A taxonomy organizes KPI types. A conceptual model explains relations among concepts. A matrix displays dimensions together. The decision framework adds ordered selection from available operational data. Manufacturing level and measurement boundary set scale and scope. Data type and input availability define possible calculations. KPI type comes after these checks because a relevant label may need variables missing from the dataset. This order protects the selection from attractive KPI names with weak operational support. It turns KPI choice into a controlled sequence of decisions and separates literature relevance from practical usability.

The framework needs standard alignment because the selected KPI must remain interpretable beyond the local dataset. The standards serve as interpretation rules for KPI meaning and standard relevance. ISO 50001 defines energy performance as measurable results related to energy efficiency, energy use, and energy consumption. It connects EnPIs

with energy baselines, relevant variables, normalization, and energy data collection (ISO 50001 2018). ISO 22400 gives the operational structure needed for manufacturing KPI interpretation. It links KPI use to scope, formula, unit, timing, audience, production methodology, and use conditions (ISO 22400-1 2014). These standard logics keep the shortlist connected to energy performance meaning and operational interpretability.

The framework's practical value comes from its starting point. The user uses available operational data. The data may include power signals, time stamps, machine identifiers, or event records. It may lack output quantities, state labels, baseline values, subsystem measurements, or material variables. In this setting, a general KPI library gives many candidates and limited selection logic. Operational KPI use depends on runtime data, computable variables, event records, and formula execution (Ramis Ferrer et al. 2018). The framework gives a stricter route. It identifies calculable KPIs, marks missing input conditions, and removes candidates outside scope. Its output is a defensible shortlist for the dataset. This supports companies, researchers, and energy teams in translating extracted KPI evidence into monitoring design, energy performance analysis, and data planning.

6.2 Framework Structure and Decision Logic

The framework is designed as a decision process based on available inputs. It helps a user move from an operational dataset to a defensible KPI shortlist. The starting point is the data situation of the user. The framework first identifies the operational scope of the data. It then checks data structure and calculation inputs. This order reduces the risk of selecting KPI names that look relevant and lack the data conditions needed for calculation or interpretation.

Step 1 and Step 2 define scale and scope. Step 1 selects the manufacturing level at machine, process, or line level. This sets the scale at which the KPI can be interpreted. The same KPI name can carry different meanings at a machine subsystem, process step, or production line. Step 2 defines the measurement boundary. Boundary specifies the measured object. Two machine level datasets may differ when one covers the whole machine and another covers a spindle or subsystem. Placing boundary after level prevents different measurement scopes from being treated as equivalent. Step 3 checks the data type group. This step defines the form of available data. Time-resolved data supports state and profile KPIs. Aggregated data suits total energy use, specific energy consumption, and line level comparison. Derived and

indirect data can support calculated indicators with lower interpretation confidence. Data type is checked before input matching because data granularity changes the KPI forms that the same input can support.

Step 4 and Step 5 check input availability. Step 4 defines the broad input pattern, such as energy or power only, energy with time, energy with output, or energy with state. Step 5 checks the exact calculation variables. This two-step check is needed because a broad input group alone is insufficient for reliable KPI selection. KPI type comes after scope and input checks. It organizes the remaining candidates by analytical form after data compatibility has been checked. Industry context remains outside the main sequence. It is used as an optional narrowing filter after the candidate KPI shortlist has been generated. This prevents useful generic KPIs from being removed too early. Figure 23 presents the central decision path and the correction routes used when the shortlist is empty or too large.

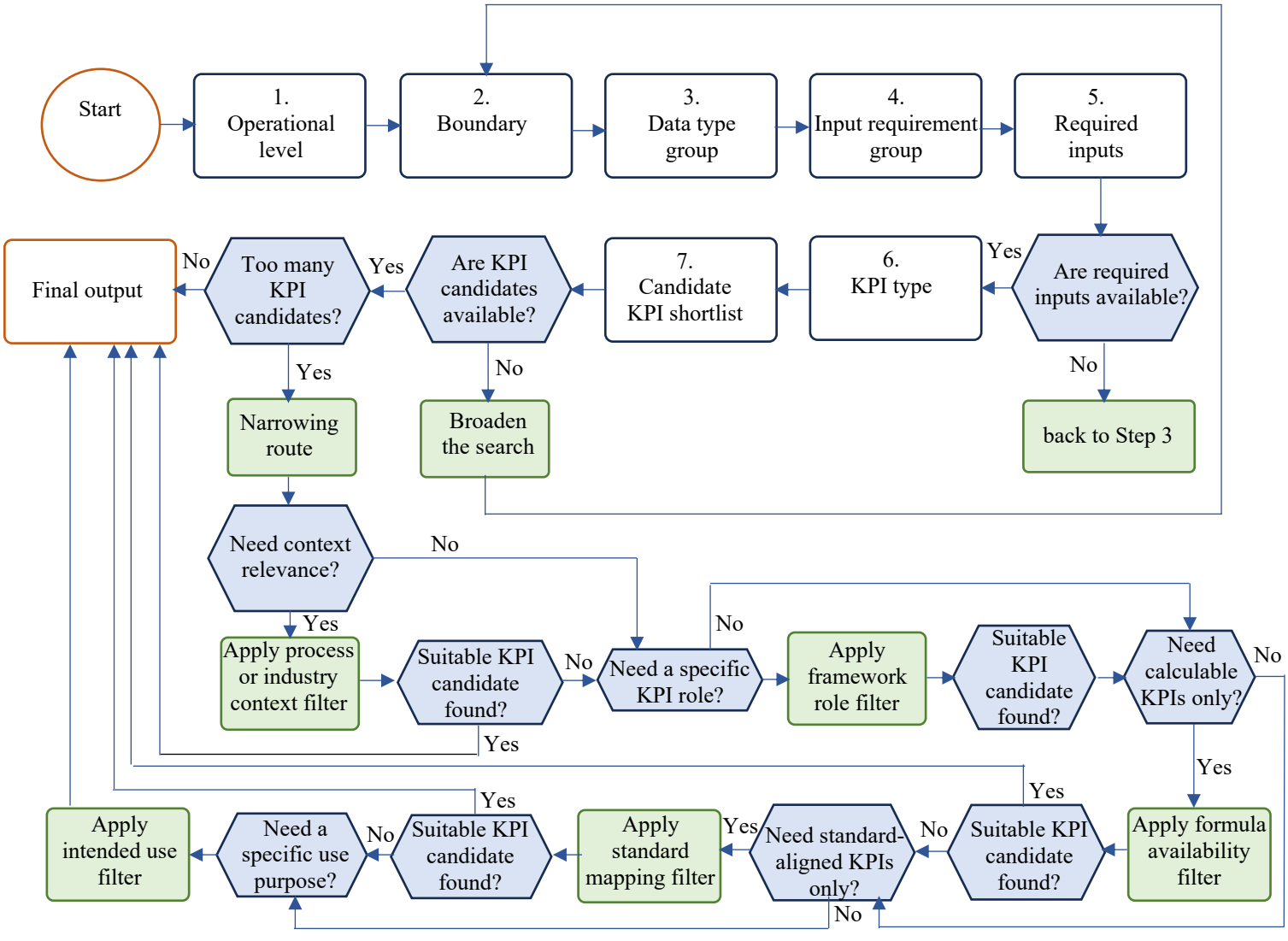

Figure 23. Input-based decision framework for selecting usable energy KPIs from operational data.

Figure 23 is read from the central path first. Step 1 selects the operational level of the available dataset and directs the user to the corresponding level table (Appendix 7). Step 2 defines the measurement boundary. Step 3 checks the data type group. Step 4 checks the input requirement group. Step 5 checks the exact required inputs. If the required inputs are available, the user proceeds to Step 6. If they are unavailable, the user returns to Step 3, relaxes the restrictive data type choice, and repeats Step 4 and Step 5. For example, a dataset without production output should move from KPI entries requiring energy with output to entries requiring energy or power only, or to time or state entries when those variables are available.

Step 6 organizes the remaining candidates by KPI type. This step uses the taxonomy results after level, boundary, data type, and input compatibility have already limited the candidate pool. Step 7 produces the candidate KPI shortlist. The main chapter reports representative KPI names. Excerpts from selection tables used in the central path are listed separately (Appendix 7). An excerpt from additional traceability fields used for interpretation and narrowing are included in the KPI-level traceability table (Appendix 6).

The next check asks if KPI candidates are available. If no candidate remains, the broadening route is used. The user returns to the earliest restrictive choice and broadens the search by widening the boundary, accepting a broader data type group, selecting a more general input requirement group, or using a more generic KPI type. This route prevents useful KPI candidates from being rejected too early.

If candidates remain, the next check asks if the shortlist is too broad. If the shortlist is acceptable, the user moves to the final output. If the shortlist is too broad, the narrowing route is used. Industry or process context is used only when context relevance is needed. Framework role narrows the shortlist by analytical function. Formula availability keeps entries with an explicit formula or inferable calculation logic. Standard mapping keeps entries linked to the selected thesis standards. Intended use narrows the shortlist by practical purpose, such as monitoring, comparison, diagnosis, optimization, baseline assessment, or improvement evaluation. The final output is a usable KPI shortlist for the user dataset. The shortlist is a result of level, boundary, data type, input, KPI type, and optional narrowing decisions. It differs from a general KPI catalogue.

6.3 Framework Application and Practical Interpretation

This section applies the decision framework in Figure 23 to an illustrative operational dataset. The section shows the movement from a defined data situation to a KPI shortlist. The dataset is used as an application case, not as a full test of all framework paths. The case dataset is the Cyber-Physical System Power Consumption dataset published on Zenodo. It contains time-resolved power data for five hydroforming production machines and annotation files for production window analysis (Iuhasz & Fortis 2024).

The dataset enters the framework at machine level because each power file represents one production machine. The boundary is treated as individual machine or machine level system. The data type is time-resolved measured power data with support from aggregated production window annotations. The annotation file provides device ID, start time, end time, product ID, cycle time, quantity produced, quantity scrap, and interruption minutes. These fields allow the framework to identify power KPIs, energy over time KPIs, production window energy KPIs, and output normalized KPIs. Table 21 shows that the illustrative dataset supports the machine level path of the framework. The dataset supports power KPI selection, time window KPI selection, and output normalized KPI selection. Subsystem KPI paths need subsystem sensor data. Line level KPI paths need line structure data. Material removal KPI paths need machining process variables. Environmental KPI paths need environmental factors or emission data.

Table 21. Application of the decision framework to the illustrative dataset.

Framework step	Selection for the illustrative dataset	Dataset evidence	Implication for KPI selection
Operational level	Machine level	Each power file represents one production machine. Device IDs are mapped to hydroforming machines in scamp_devices.csv.	The framework uses machine-level KPI entries (Appendix 7).
Boundary	Individual machine or machine-level system	The power data are linked to individual machines such as Hydroforming 9, Hydroforming 5, Hydroforming 8, Hydroforming 4, and Hydroforming 12.	Subsystem-specific and line-level KPIs are excluded unless additional boundary data are available.
Data type group	Time-resolved measured data supported by aggregated annotation	The power files provide timestamped power measurements. scamp_report_3m.csv provides production-window annotations.	The dataset supports power profiles, energy-over-time KPIs, and production-window KPIs.
Input requirement group	Energy or power only; energy plus time; energy plus production output	Power data can be combined with Start Time, End Time, and Quantity Produced.	The framework can select power-based, time-window-based, and output-normalized KPIs.
Required inputs	Power, timestamp, device ID, start time, end time, produced quantity, scrap quantity, interruption minutes	These fields are available across the power files, scamp_devices.csv, Data.zip, and scamp_report_3m.csv.	KPIs requiring material removal, process parameters, subsystem sensors, line structure, or emission factors are not directly supported.
KPI type	Power and demand KPI; absolute energy consumption; specific or intensity-based energy KPI	The dataset supports power values, energy aggregation over time, and normalization by produced quantity.	The dataset supports power demand KPIs, energy consumption KPIs, and output normalized energy KPIs. These candidates can be reported using mean power, peak power, total energy, and energy per product.
Candidate KPI shortlist	Machine-level energy and power KPIs	The shortlist is derived from the compatible paths above.	The final candidates are interpreted using the KPI level table (Appendix 6).

Based on the framework paths reported in Table 21 the first execution used one selected machine from the dataset. The selected device was Hydroforming 8. It corresponds to Device ID 170. The path used the machine level route. The boundary was set to individual machine. The data type group was set to time-resolved measured data. The input requirement group was set to energy or power only. The required inputs were timestamped power measurements

and a machine or device identifier. These selections left two KPI types. They were power and demand KPI and absolute energy consumption. The filtering process resulted in nine KPI candidates. Table 22 reports these framework selected KPI candidates and explains their operationalization for the selected machine dataset. Some KPI labels in Table 22 appear similar because they originate from different source papers but passed the same machine-level filtering path. The first path shows that the framework does not treat all machine level energy KPIs as equally usable. It retained KPI candidates that matched the available power signal. It excluded candidates that required production output process variables subsystem data or environmental inputs.

Table 22. Operationalization of framework-selected KPI candidates for the selected machine dataset.

Selected KPI candidate	KPI type in extraction	Operational KPI family in dataset	Reporting approach
Device electrical power demand	Power and demand KPI	Power-demand signal	Report mean power and peak power from power time series
Real-time machine power demand	Power and demand KPI	Power-demand signal	Report mean power and peak power from power time series
Power consumption	Power and demand KPI	Power-demand signal	Report mean power and peak power from power time series
Real-time machine energy consumption	Power and demand KPI	Power-demand signal	Use power time series as monitored signal; integrate over time if reported as energy
Real-time machine power demand	Power and demand KPI	Power-demand signal	Report mean power and peak power from power time series
Energy consumption	Absolute energy consumption	Energy-consumption measure	Integrate power over time and report total energy
Power consumption	Power and demand KPI	Power-demand signal	Report mean power and peak power from power time series
Machine-level electricity consumption	Absolute energy consumption	Energy-consumption measure	Integrate power over time and report total energy
Active power used as reference value	Power and demand KPI	Power-demand reference signal	Use power as reference signal if it represents active power

For the numerical application, the Hydroforming 8 power time series came from the original data.zip file. The raw machine file was processed in Python and produced a cleaned file named clean_timeseries_fixed.csv. The processed file contained three fields: time, power, and state. KPI calculations used the power column as the machine level power signal and the time column as the timestamp basis. Power demand candidates were operationalized with summary statistics of the power signal. Mean power was 1296.23 W, and peak power was

2194 W. Energy consumption candidates were operationalized by integrating the power signal over time. The result was 21.51 kWh for the selected machine dataset. This result shows the lower analytical limit of the framework application. With power data alone, the framework can support machine energy monitoring. It cannot explain energy performance per produced unit until production output is added.

The second execution path used the same machine level starting point as the first path. The selected device was Hydroforming 8, and the boundary was individual machine. The initial data type group was time-resolved measured data. The required input check retained no suitable KPI candidates for the production output path. The correction route sent the selection back to Step 3. The data type group was broadened, and the restrictive time-resolved data filter was removed. This shows the correction logic in use. When the first strict path gives no candidate, the framework broadens the data type choice and checks the input structure again.

The input requirement group was then set to energy plus production output. This broader path retained derived and indirect KPI entries that combine machine energy with production output information. The resulting shortlist was narrowed to three KPI candidates suitable for operationalization with the selected machine dataset.

Table 23 summarizes the operationalization of these three-production output KPI candidates. The second path shows the filtering value of the framework. Several production output KPI candidates were excluded because they required value added energy, waste energy, material removal energy, historical benchmark values, OEE components, or auxiliary electricity separation. These inputs were absent from the illustrative dataset. This result shows that the framework prevents unsupported KPI names from being reported as usable KPIs. This is a key difference between KPI listing and KPI selection. A KPI name may look relevant at machine level. It becomes usable only when the dataset contains the exact inputs needed for calculation.

Table 23. Operationalization of production-output-based KPI candidates for the selected machine dataset.

Selected KPI candidate	KPI type in extraction	Operationalization for this dataset	Reporting approach
Total machine energy use per product	Specific / intensity-based energy KPI	Integrate the machine power signal over a production window and divide it by Quantity Produced.	Report energy per produced unit.
Average energy consumption of a production cycle	Absolute energy consumption	Operationalize the KPI as selected example-cycle energy by integrating the machine power signal over the example-cycle window from scamp_patterns.csv.	Report selected example-cycle energy; not the average over all production cycles.
Energy indicator	Energy efficiency ratio	Calculate energy per product for selected production windows and divide the minimum observed energy-per-product value by the comparison-window value.	Report dataset-derived energy indicator.

After Table 23 defines the KPI operationalization, the calculation is carried out for Hydroforming 8. The power signal comes from the processed time series file clean_timeseries_fixed.csv. The production window information comes from scamp_report_3m.csv. The required fields are Start Time, End Time, Quantity Produced, Quantity Scrap, and Interrupt Minutes. The selected example cycle window comes from scamp_patterns.csv. For each production window, energy is calculated by integrating the power signal over the selected time interval. Total machine energy use per product is calculated by dividing the production window energy by Quantity Produced.

The KPI named average energy consumption of a production cycle is treated with caution because the dataset provides only selected example cycle boundaries. It is operationalized for the selected example cycle window available in scamp_patterns.csv. It is not reported as the average of all production cycles. This treatment keeps the calculation aligned with the available dataset and prevents reporting a cycle average that the data cannot fully support.

The dataset derived energy indicator is calculated by dividing the minimum observed energy per product value by the energy per product value of the comparison window. Table 24 reports the calculated KPI results for the selected machine dataset.

Table 24. Calculated KPI results for the selected machine dataset.

Calculated measure	Value	Unit	Basis
Energy of selected production window	1.25480	kWh	Window 1
Total machine energy use per product	0.00427	kWh/product	Window 1
Energy of selected example cycle	0.00868	kWh	Selected example pattern
Energy of second selected production window	1.34954	kWh	Window 2
Total machine energy use per product, second window	0.00444	kWh/product	Window 2
Dataset-derived energy indicator, second window	0.96142	-	Minimum observed value / second-window value

Table 24 shows similar output normalized energy use across the selected production windows. The first window had 0.00427 kWh per product. The second window had 0.00444 kWh per product. The second window used about 4.0 percent more energy per product than the minimum observed window. The dataset derived energy indicator of 0.9614 shows that the second window remained close to the best observed value in the selected examples.

This comparison shows the added value of production output data. The same power signal first supported energy monitoring. After connection to Quantity Produced, it supported output normalized interpretation. This confirms the practical role of the framework. The framework separates usable KPI candidates from unsupported KPI names. It also links selected KPI candidates to measurable dataset variables and calculated results.

This link is the main analytical result of the application because it connects the taxonomy based KPI entries to actual operational data fields. The comparison between the two paths shows that KPI usability depends on the available input structure. KPI names alone are insufficient. The remaining framework paths were excluded from numerical calculation because their required inputs were absent from the dataset.

7 Discussion

This chapter interprets review and framework findings in relation to previous research, energy management, and digital KPI architecture. It develops one main argument. Energy KPI evidence in discrete manufacturing is broad. Its value depends on controlled interpretation. The discussion connects this argument to KPI role, boundary, data support, standard relevance, and practical selection logic.

7.1 Synthesis of Key Findings

Section 4.2 shows a clear strength in the reviewed literature. Direct energy KPIs dominate across manufacturing contexts and give strong energy visibility. Section 4.7 adds the role dimension and changes the interpretation of this strength. The same KPI base contains measurement evidence, decision evidence, and supporting evidence. This distinction matters because a measurement signal can be read as a decision KPI, and a supporting indicator can be read as direct energy performance evidence. A taxonomy can organize KPI types. A framework is needed to control the movement from reported indicator to usable evidence and to separate KPI roles during selection.

Direct KPI dominance changes across the evidence base. It first changes across manufacturing contexts. Forming and metal shaping had 88.2% direct KPIs, and assembly lines had 62.5%. It also changes across measurement boundaries. Machine subsystem had 93.3% direct KPIs, and individual machine had 74.5% with a higher supporting share. This pattern shows that directness is shaped by production context and measurement boundary. A direct energy KPI can need different supporting context according to the measured object. Manufacturing level defines the scale of interpretation. Measurement boundary defines the measured object. This distinction explains the first order of the framework. Level is checked before boundary so the framework defines the claim scale first and then defines the evidence source behind that claim. This order reduces weak comparison between KPIs with the same level label and different measurement scopes.

Section 4.4 indicates that measurement boundary and interpretation level can differ. Section 4.6 adds a second constraint. Many KPI entries are constructed evidence instead of raw measured values. The largest group combined derived and indirect data with formula calculation and included 258 KPI entries. KPI evidence is often produced by calculation, aggregation, modelling, state logic, and baseline comparison. A clear boundary defines the measured object. It does not define the usable evidence form. Data type is needed at this point because it shows the structure and granularity of available evidence. Time-

resolved data can support profiles, states, and events. Aggregated and derived data support different KPI claims with different interpretation strength. This explains the position of data type in the framework after level and boundary, and before input matching. The framework first defines the claim scale and measured object. It then checks the evidence form that can support calculation.

Input checks are needed before KPI type selection because KPI types carry different calculation burdens and input needs. The formula results make this difference clear. Efficiency and intensity KPIs had the strongest explicit formula basis with 68% of entries reporting a formula. Improvement and savings KPIs relied mainly on inferable calculation logic with 59% inferable logic and 24% explicit formula reporting. Composite and hybrid KPIs had a higher weak or incomplete calculation basis at 18%. These differences show that KPI type is more than an analytical label. It carries a required input structure and a different level of calculation support. A KPI can be relevant to energy performance and remain unusable in a specific dataset if output data, baseline value, state label, or component variable is missing. The framework checks input requirement and required inputs before KPI type so selection starts from data support and then moves to analytical grouping. This order protects the shortlist from attractive KPI names with missing calculation support.

Standard relevance needs controlled interpretation. Section 4.5 supports this point. Only 6.9% of KPI entries had an explicit link to one selected thesis standard, and 72.3% required conceptual thesis standard mapping. A rule limited to explicit standard mentions would remove a large part of standard relevant evidence. Broad conceptual mapping can also create weak standard claims. The mapping results show this tension. ISO 50001 covered 78% of KPI entries. ISO 22400 covered 15%, and ISO 20140 covered 29%. Each standard therefore needs a different interpretation threshold. This explains the place of standard mapping in the narrowing route after candidate KPI selection. At that point the framework has already

checked level, boundary, data type, and inputs. Standard mapping can then work with formula availability, framework role, and intended use to keep KPI candidates with defensible standard claims.

The Hydroforming 8 application confirms the same selection problem in a real data setting. Power data supported mean power, peak power, and total energy with 1296.23 W, 2194 W, and 21.51 kWh. These outputs supported machine level monitoring. Product-level interpretation became possible after production output was added and produced 0.00427 and 0.00444 kWh per product. Each added input can change the strength and type of KPI claim. The broadening and narrowing routes respond to this condition. Broadening prevents early exclusion of usable KPI candidates after an overly restrictive choice. Narrowing prevents large candidate lists from becoming weak metric collections. Together these routes make the framework a controlled selection logic instead of a KPI catalogue.

7.2 Interpretation in Relation to Previous Research

Previous research places industrial energy efficiency inside operational performance. Energy efficiency measures can affect production quality and throughput and downtime and maintenance and working conditions and emissions. This view treats energy work as part of the production system (Cagno et al. 2022). This thesis extends that view from energy efficiency actions to KPI evidence. Studies assess performance effects. This thesis assesses the conditions that make an energy value suitable for a performance claim. The contribution is a move from broad performance effects to controlled KPI claims at KPI entry level.

Earlier EnPI research highlights boundary definition and relevant variables and energy performance interpretation (Kanchiralla et al. 2020; Benedetti et al. 2017). This thesis applies these ideas in operational form. Boundary and manufacturing level and data basis and formula clarity and input availability are used as selection conditions. This turns EnPI principles into a route from reported indicator to usable evidence in discrete manufacturing.

Manufacturing KPI research gives importance to scope and formula and unit and timing and use context and audience (ISO 22400-1 2014). This thesis applies this logic to energy KPI selection. The main difference is the starting point. The framework starts with evidence needed for calculation and interpretation. KPI type is used after data support has been

checked. This order keeps selection tied to available data and reduces the risk of choosing indicators with strong labels and weak calculation support.

Standard mapping adds the main link with previous research. Energy management and manufacturing operations and environmental performance often appear as separate measurement areas. This thesis connects them at KPI entry level. ISO 50001 provides the energy performance basis. ISO 22400 adds manufacturing operations logic. ISO 20140 adds environmental manufacturing logic. The contribution is a controlled link between the standards and each KPI entry. Standard relevance is treated as an interpretive claim. It needs definition and calculation support and boundary and role and intended use.

Digital manufacturing research emphasizes monitoring and data collection and energy visibility. This thesis accepts the need for visibility and adds a stricter condition. Digital data become KPI evidence after meaning and data support are controlled. The Hydroforming 8 application illustrates this point. Power data supported monitoring and energy aggregation. Production output changed the claim toward product level energy performance. This shows the practical value of the framework as a bridge between digital measurement and defensible KPI evidence.

Overall previous research provides the conceptual basis for energy performance and EnPI design and manufacturing KPI structure and standards and digital monitoring. This thesis connects these streams in one KPI selection logic. Its main contribution is the move from broad performance concepts to KPI entry level evidence for classification and standard interpretation and practical use in discrete manufacturing.

7.3 Implications for Energy Management in Manufacturing

The findings have direct implications for energy management in manufacturing. The main implication is disciplined KPI use. Energy managers should define the performance claim before selecting an energy KPI. A power value or energy value supports management after its boundary and manufacturing level and calculation logic and input variables and decision purpose are defined (ISO 50001 2018; Kanchiralla et al. 2020). This approach links KPI selection to the evidence required for that claim. It reduces weak KPI reporting and helps energy teams avoid indicators with unclear management value.

The second implication concerns data planning. Energy management data should follow the intended performance claim. Power data can support machine monitoring and load analysis. Time data can support energy aggregation over a selected period. Production output can support product level energy interpretation. State labels can support state level analysis. Baseline values can support savings and improvement assessment. This logic makes data collection more focused because each KPI claim requires a specific input structure.

The Hydroforming 8 application in section 6.3 shows the management limit of power data. Mean power of 1296.23 W and peak power of 2194 W support load monitoring and peak demand awareness. These values show machine behavior. Their management claim remains limited to energy visibility. They do not explain production efficiency or product level performance. The excluded KPI candidates show the same limit. Stronger claims need stronger input support. Production output, process variables, subsystem data and environmental inputs define the next interpretation level. This gives energy management a practical rule. Stronger performance claims need stronger input support. The framework helps energy teams separate energy visibility from stronger KPI claims.

The third implication concerns standard use. Standards can control the meaning of KPI claims. ISO 50001 supports energy performance claims. ISO 22400 supports manufacturing operations claims. ISO 20140 supports environmental manufacturing claims (ISO 20140-1 2019; ISO 22400-1 2014; ISO 50001 2018). These standards should guide KPI portfolios because energy claims and operational claims and environmental claims need different evidence. A KPI portfolio becomes stronger after each indicator has a defined standard role and a clear data basis.

The final implication concerns practical KPI portfolio design. Manufacturing firms should separate measurement signals and supporting indicators and decision KPIs. Measurement signals show energy and power behavior. Supporting indicators explain state and output and downtime and quality and process context. Decision KPIs support comparison and prioritization and improvement and reporting. This separation helps energy teams build KPI systems with clear roles. The proposed framework supports this task by linking KPI candidates to data inputs and formula availability and boundary and standard role. This gives energy management a clear route from measured data to defensible performance evidence.

7.4 Implications for Digital KPI Architecture in Smart Manufacturing Systems

Smart manufacturing systems strengthen energy visibility, awareness, connectivity, and visualization, supporting energy monitoring, performance evaluation, and energy efficient process design in manufacturing (Cagno et al. 2025). This thesis adds that digital systems need KPI meaning before metric generation. Sensors, machines, and production platforms can produce many values. Performance evidence appears after each value is linked to boundary, production level, calculation logic, standard role, and decision use. This is central for dashboards and digital twins because unclear boundary, input source, formula, role, or intended use can turn displayed values into weak performance claims. Each KPI record should include boundary, level, formula, unit, input source, update frequency, standard role, and intended use. These elements turn a displayed value into traceable performance evidence. ISO 22400 supports this logic because manufacturing KPIs need defined scope, formula, unit, timing, and use context (ISO 22400-1 2014).

The findings support a four-layer KPI architecture for smart manufacturing systems. The first layer contains measurement signals. The second layer adds production context. The third layer produces calculated KPI evidence. The fourth layer connects KPI evidence to monitoring, comparison, reporting, and improvement decisions. This structure separates raw signals from performance claims and keeps a clear difference between measured data, contextual data, and decision evidence. Its value lies in claim control. Digital systems increase measurement speed and data volume. They can also increase weak interpretation under missing KPI rules. The proposed framework reduces this risk by checking candidate KPIs against data inputs, formula availability, boundary, and standard role before practical use. Table 25 synthesizes Chapter 7 by linking KPI interpretation, previous research, energy management use, and digital KPI architecture to the thesis contribution.

Table 25. Analytical synthesis of Chapter 7 discussion

Discussion focus	Evidence used in Chapter 7	Analytical interpretation	Implication for the thesis contribution
KPI interpretation	Section 7.1 combines direct KPI dominance, supporting KPI shares, framework roles, formula availability, standard relevance and the Hydroforming 8 application.	Energy KPI evidence is broad. Its value depends on role, boundary, data support, formula clarity, standard relevance and input availability.	The thesis explains the need for a controlled framework that turns reported KPI entries into usable KPI evidence.
Relation to previous research	Section 7.2 connects earlier research on energy efficiency, EnPIs, manufacturing KPIs, standards and digital monitoring.	Previous research provides the conceptual basis. This thesis connects these streams at KPI entry level and links them to selection logic.	The thesis adds a controlled interpretation path for classification, standard mapping and practical KPI use.
Energy management use	Section 7.3 links KPI selection with claim discipline, data planning, standard use and KPI portfolio design.	Energy managers should define the performance claim and then check the data needed to support it.	The thesis gives a practical rule for moving from energy visibility to defensible performance evidence.
Digital KPI architecture	Section 7.4 links smart manufacturing data, dashboards, KPI layers and decision evidence.	Digital systems can make weak metrics look reliable if boundary, input source, formula, role and intended use remain unclear.	The thesis supports a digital KPI architecture that filters raw data into traceable decision KPIs.

Overall, Chapter 7 builds one argument across four levels. Energy KPI value depends on controlled interpretation. This interpretation links literature synthesis, previous research, energy management use and digital KPI architecture. The chapter shows that the thesis turns reported indicators into defensible KPI evidence for energy management and smart manufacturing systems.

8 Conclusion

This chapter concludes the thesis by answering the research questions and presenting the main contributions, limitations, and future research directions. It brings together the review results, KPI taxonomy, standard mapping, and framework application. Its main purpose is to show the movement from reported energy KPI entries to usable performance evidence in discrete manufacturing.

8.1 Summary of Findings and Answers to Research Questions

This section returns to the four research questions set in Chapter 1 and gives a compact answer to each question. Table 26 presents the main findings from the systematic review, KPI taxonomy, standard mapping, and Hydroforming 8 application. It shows the analytical path from reported energy KPI evidence to taxonomy development and practical testing with operational data.

Table 26. Summary of findings by research question.

Research question	Main answer	Key evidence
RQ1	The review found a large and mixed energy KPI evidence base in discrete manufacturing. The reported KPIs included direct energy KPIs and supporting KPIs.	The final review included 76 studies and 737 KPI entries. Direct KPIs measured energy consumption, power demand, energy efficiency, energy saving and energy loss. Supporting KPIs explained output, machine state, downtime and process context.
RQ2	The thesis structured the extracted KPI evidence into six analytical groups. The taxonomy separates KPI type from manufacturing level, measurement boundary, data type and framework role.	The six groups are absolute energy consumption, power and demand, normalized and efficiency KPIs, improvement, savings and loss KPIs, state and time KPIs, and composite, hybrid and context specific KPIs.
RQ3	ISO 50001 gave the main energy performance link. ISO 22400 and ISO 20140 gave narrower complementary links for manufacturing operations and environmental manufacturing performance.	78% of KPI entries were mapped to ISO 50001. 15% were mapped to ISO 22400. 29% were mapped to ISO 20140. 72.3% received conceptual thesis standard mapping, while 6.9% had an explicit link to one selected thesis standard.
RQ4	The Hydroforming 8 application showed that practical KPI use depends on available operational inputs. Power data supported machine energy monitoring. Production output supported product level energy interpretation.	The application produced 1296.23 W mean power, 2194 W peak power and 21.51 kWh total energy. Adding production output produced 0.00427 and 0.00444 kWh per product.

Table 26 brings the four research questions into one analytical path. RQ1 establishes the energy KPI evidence base, RQ2 turns this evidence into a taxonomy, RQ3 adds standard interpretation, and RQ4 tests the selection logic with operational data. This sequence gives the main result of the thesis. Energy KPI value depends on controlled interpretation across boundary, manufacturing level, calculation logic, standard role, and input support. The thesis moves from reported indicators to usable performance evidence. A KPI becomes stronger after its measured object, calculation basis, data inputs, and standard role are clear. Discrete manufacturing needs energy KPI selection that links literature evidence to defensible operational use.

8.2 Contributions of the Thesis

The main contribution of this thesis is the movement from reported energy KPI entries to controlled KPI evidence in discrete manufacturing. This movement combines the systematic review, KPI taxonomy, standard mapping, and practical selection framework. The review creates the evidence base at KPI entry level. The taxonomy organizes this evidence by analytical meaning and separates KPI type from manufacturing level, measurement boundary, data type, and framework role. This separation clarifies KPI entries with similar names and different operational meanings.

Standard mapping extends this evidence into standard interpretation. It connects extracted KPI entries with ISO 50001, ISO 22400, and ISO 20140. It shows the energy performance role, manufacturing operations role, and environmental manufacturing role of the extracted indicators. Standard relevance is treated as an interpretation task that needs definition, calculation support, boundary, role, and intended use.

The framework turns classified and mapped KPI evidence into practical selection logic. It starts from available operational data and checks level, boundary, data type, and required inputs before KPI type selection. The Hydroforming 8 application shows this contribution in use. The framework separates calculable KPI candidates from unsupported KPI names and links selected KPIs to measurable dataset variables.

Together these contributions make the thesis more than a review of reported indicators. The thesis provides a structured route from literature evidence to defensible KPI evidence for classification, standard interpretation and practical use in discrete manufacturing.

8.3 Limitations and Future Research Directions

This study has four main limitations. First, the review depended on the reporting quality of the selected studies. Some articles reported clear KPI names, units, inputs, boundaries, and calculation logic. Other articles gave incomplete KPI detail. This condition affected extraction, classification, and standard mapping. Future research can develop a minimum reporting template for energy KPIs in manufacturing. The template should define KPI name, unit, boundary, manufacturing level, input variables, formula, data source, and intended use.

Second, some classification and standard mapping decisions required interpretation. The thesis used predefined rules to reduce inconsistent coding. Interpretive judgment was needed for KPIs with unclear boundary, mixed role, or limited calculation detail. Future research can strengthen this part with expert review and repeated coding by several researchers. This work can test the stability of the taxonomy, framework roles, and standard mapping logic.

Third, the empirical application had limited scale. The framework was demonstrated with one real operational dataset. The Hydroforming 8 application showed practical feasibility with power and production data but covered one machine context and one data setting. Future research should apply the framework to several company datasets from different machines and production contexts. This can show its value in real energy management settings and support comparison across company data structures.

Fourth, the selected dataset had missing inputs. It supported power monitoring, total energy calculation, and energy per product calculation. It lacked subsystem signals, material removal variables, baseline values, environmental factors, and detailed process parameters. Future research should use richer operational datasets from power meters, machine logs, production records, maintenance records, and environmental data. These inputs should be linked to the required input fields in the framework to support stronger KPI calculation and better energy management decisions.

Future research can connect the framework with Artificial Intelligence (AI) and machine learning (ML) applications. ML can support operating state detection, energy demand prediction, anomaly detection, and KPI candidate recommendation. These outputs should remain linked to KPI definitions, required inputs, standard mapping rules, and framework roles. AI models can produce useful predictions and weak KPI claims in the same system.

The framework can help companies use model outputs as controlled KPI evidence for monitoring and energy performance management.

Another direction is the development of company KPI systems from the framework. Future work can embed the framework in dashboards or digital twin environments. The system can read available data fields, suggest calculable KPIs, show missing inputs, and mark possible standard links. This can turn the framework from a thesis method into a practical tool for energy teams.

In conclusion, this thesis shows that energy KPI selection in discrete manufacturing requires controlled evidence. Reported indicators gain practical value after boundary, level, data basis, inputs, calculation logic, standard role, and intended use are defined. The proposed taxonomy and framework support this task by connecting literature evidence with operational data and standard interpretation. This gives companies a practical basis for KPI systems that move from energy visibility to defensible energy performance evidence.

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Appendix 1. Primary database search strings

This appendix presents the full exact search strings used in the primary database searches conducted in **Scopus** and **Web of Science**. These searches formed the core of the structured literature identification process and were implemented through an initial broad search followed by refinement searches targeting specific operational levels in discrete manufacturing.

1.1 Scopus searches

Run ID: S01
Database: Scopus
Date searched: 11 February 2026
Search purpose: Broad primary search
Exact query:
TITLE-ABS-KEY (("energy KPI*" OR "energy key performance indicator*" OR "energy performance indicator*" OR EnPI* OR "energy metric*" OR "energy indicator*") AND (manufactur* OR "industrial" OR "production" OR "factory" OR "machine tool*" OR machining OR "production equipment" OR "industrial equipment"))
Filters applied: Publication years 2015-2026; journal articles and conference papers; English language
Results retrieved: 524

Run ID: S01a
Database: Scopus
Date searched: 11 February 2026
Search purpose: Machine-level refinement search
Exact query:
TITLE-ABS-KEY (("energy KPI*" OR "energy key performance indicator*" OR "energy performance indicator*" OR EnPI* OR "energy metric*" OR "energy indicator*") AND (manufactur* OR "industrial" OR "production" OR "factory" OR "machine tool*" OR machining OR "production equipment" OR "industrial equipment") AND ("machine-level"

OR equipment OR machin* OR "workstation" OR "asset-level") AND ("time series" OR timeseries OR "real-time" OR realtime OR sensor* OR "process data" OR "operational data" OR PLC OR SCADA OR MES))

Filters applied: Publication years 2015-2026; journal articles and conference papers; English language

Results retrieved: 23

Run ID: S01b

Database: Scopus

Date searched: 24 February 2026

Search purpose: Process-level refinement search

Exact query:

TITLE-ABS-KEY (("energy KPI*" OR "energy key performance indicator*" OR "energy performance indicator*" OR EnPI* OR "energy metric*" OR "energy indicator*") AND (manufactur* OR "industrial" OR "production" OR "factory" OR "machine tool*" OR machining OR "production equipment" OR "industrial equipment") AND ("process" OR "process-level" OR "unit operation*" OR "production process*" OR "process step*" OR "operation*" OR "manufacturing process*") AND ("time series" OR timeseries OR "real-time" OR realtime OR sensor* OR "process data" OR "operational data" OR PLC OR SCADA OR MES))

Filters applied: Publication years 2015–2026; journal articles and conference papers; English language

Results retrieved: 27

Run ID: S01c

Database: Scopus

Date searched: 26 February 2026

Search purpose: Line-level and cell-level refinement search

Exact query:

TITLE-ABS-KEY (("energy KPI*" OR "energy key performance indicator*" OR "energy performance indicator*" OR EnPI* OR "energy metric*" OR "energy indicator*") AND (manufactur* OR "industrial" OR "production" OR "factory" OR "machine tool*" OR machining OR "production equipment" OR "industrial equipment") AND ("production

line" OR "production-line" OR line-level OR "line level" OR "assembly line" OR "manufacturing line" OR "work cell" OR "cell-level" OR "shop floor" OR "production system" OR "manufactoring system" OR "workstation network") AND ("time series" OR timeseries OR "real-time" OR realtime OR sensor* OR "process data" OR "operational data" OR PLC OR SCADA OR MES))

Filters applied: Publication years 2015–2026; journal articles and conference papers; English language

Results retrieved: 1

1.2 Web of Science searches

Run ID: S02

Database: Web of Science

Date searched: 11 February 2026

Search purpose: Broad primary search

Exact query:

("energy KPI" OR "energy performance indicator" OR EnPI OR "energy metric") AND (manufactur* OR industrial OR production OR factory OR "machine tool" OR machining OR "production equipment" OR "industrial equipment")

Filters applied: Publication years 2015-2026; journal articles and proceedings papers; English language

Results retrieved: 134

Run ID: S02a

Database: Web of Science

Date searched: 11 February 2026

Search purpose: Machine-level refinement search

Exact query:

("energy KPI" OR "energy performance indicator" OR EnPI OR "energy metric") AND (manufactur* OR industrial OR production OR factory OR "machine tool" OR machining OR "production equipment" OR "industrial equipment") AND (machine OR equipment OR workstation OR "machine-level" OR "asset-level") AND ("time series" OR timeseries OR

realtime OR "real-time" OR sensor* OR "process data" OR "operational data" OR SCADA OR PLC OR MES)

Filters applied: Publication years 2015-2026; journal articles and proceedings papers; English language

Results retrieved: 94

Run ID: S02b

Database: Web of Science

Date searched: 26 February 2026

Search purpose: Process-level refinement search

Exact query:

("energy KPI" OR "energy performance indicator" OR EnPI OR "energy metric") AND (manufactur* OR industrial OR production OR factory OR "machine tool" OR machining OR "production equipment" OR "industrial equipment") AND ("process" OR "process-level" OR "unit operation*" OR "production process*" OR "process step*" OR "operation*" OR "manufacturing process*") AND ("time series" OR timeseries OR realtime OR "real-time" OR sensor* OR "process data" OR "operational data" OR SCADA OR PLC OR MES)

Filters applied: Publication years 2015–2026; journal articles and proceedings papers; English language

Results retrieved: 97

Run ID: S02c

Database: Web of Science

Date searched: 26 February 2026

Search purpose: Line-level and cell-level refinement search

Exact query:

("energy KPI" OR "energy performance indicator" OR EnPI OR "energy metric") AND (manufactur* OR industrial OR production OR factory OR "machine tool" OR machining OR "production equipment" OR "industrial equipment") AND ("production line" OR "production-line" OR line-level OR "line level" OR "assembly line" OR "manufacturing line" OR "work cell" OR "cell-level" OR "shop floor" OR "production system" OR "manufactoring system" OR "workstation network") AND ("time series" OR timeseries OR

realtime OR "real-time" OR sensor* OR "process data" OR "operational data" OR SCADA OR PLC OR MES)

Filters applied: Publication years 2015-2026; journal articles and proceedings papers; English language

Results retrieved: 82

Appendix 2. Supplementary Google Scholar search strings

This appendix presents the supplementary **Google Scholar** searches used to improve the completeness of study identification. Google Scholar was not used as a primary database, but as a complementary search source to identify potentially relevant studies not fully captured through the structured searches in Scopus and Web of Science. Because Google Scholar does not provide the same filtering options as the primary databases, only the publication year filter was applied directly, while language and document-type eligibility were addressed during screening.

2.1 Google Scholar searches

Run ID: S03a

Database: Google Scholar

Date searched: 6 March 2026

Search purpose: Supplementary machine-level search

Exact query:

manufacturing machine OR "machine tool" OR machining OR sensor OR SCADA OR "time series" "energy performance indicator" -building -HVAC -residential -household -transportation -vehicle -grid -"smart grid" -blockchain -campus -hospital

Filters applied: Publication years 2015-2026

Results retrieved: 78

Run ID: S03b

Database: Google Scholar

Date searched: 6 March 2026

Search purpose: Supplementary process-level search

Exact query:

manufacturing "unit operation" OR "process step" OR "process planning" OR "production process" OR sensor OR SCADA OR "time series" "energy performance indicator" -building -HVAC -residential -household -transportation -vehicle -blockchain -campus -hospital

Filters applied: Publication years 2015-2026

Results retrieved: 64

Run ID: S03c

Database: Google Scholar

Date searched: 6 March 2026

Search purpose: Supplementary line-level and cell-level search

Exact query:

manufacturing ("production line" OR "assembly line" OR "manufacturing line" OR line-level OR "line level" OR cell OR "work cell" OR "shop floor") (sensor OR SCADA OR "time series") "energy performance indicator" -building -HVAC -residential -household -transportation -vehicle -blockchain -campus -hospital

Filters applied: Publication years 2015-2026

Results retrieved: 15

Appendix 3. Detailed study selection counts underlying the PRISMA 2020 flow diagram

Appendix 3 documents the detailed study selection counts used for the PRISMA 2020 flow diagram in Chapter 3. The review used two selection routes. The primary database pathway covered Scopus and Web of Science. The supplementary pathway used Google Scholar. The primary databases formed the main structured search process, while Google Scholar increased the completeness of study identification.

The two routes required different screening procedures. Records from Scopus and Web of Science usually included adequate bibliographic metadata and abstracts, so they moved directly to title and abstract screening after deduplication. Google Scholar records sometimes lacked abstracts and had limited language or document type filtering. These records first received title screening. The remaining records then moved to title and abstract screening. This modified workflow followed the review protocol, reduced early full text retrieval of clearly irrelevant records, and preserved sensitivity during screening.

Screening decisions in all pathways followed the predefined review protocol. Title and abstract screening used broad logic. A record was retained if the title or abstract indicated a discrete industrial manufacturing context, explicit energy focus, method or monitoring context related to energy, or measured operational data. Records with unclear inclusion status were coded as uncertain and moved to full text assessment. Final eligibility was confirmed at full text stage.

Full text screening applied stricter criteria. Studies were eligible if they addressed discrete manufacturing operations at machine level, process or unit operation level, or line or cell level. They had to report at least one identifiable energy KPI or Energy Performance Indicator (EnPI) suitable for structured extraction or standard mapping. The indicator had to rely on measured data, recorded data, or operationally grounded manufacturing data. Studies were excluded after failing one or more essential criteria. These criteria covered non manufacturing context, wrong operational level, lack of computable energy KPI or EnPI, conceptual only treatment, insufficient methodological detail, and non discrete manufacturing context. Table 3.1 reports the detailed study selection counts for the primary database pathway, including search waves, database specific record counts, deduplication, screening decisions, report retrieval, and final inclusion.

Table 3.1. Detailed study selection counts for the primary database pathway

Stage	Wave 1	Wave 2	Primary total	Explanation
Records identified from primary databases	117	207	324	Wave 1: 23 Scopus + 94 Web of Science. Wave 2: 28 Scopus + 179 Web of Science.
Duplicates removed before screening	1	109	110	Duplicates were merged in Zotero before screening.
Records screened by title and abstract	116	98	214	Records remaining after deduplication.
Records included at title and abstract screening	44	39	83	Records clearly meeting the title and abstract inclusion logic.
Records marked uncertain at title and abstract screening	20	12	32	Records carried forward because eligibility could not be confirmed from title and abstract.
Records excluded at title and abstract screening	52	47	99	Records clearly outside the review scope or failing title and abstract screening logic.
Reports sought for retrieval	64	51	115	Included and uncertain records were carried forward for full text retrieval.
Reports not retrieved	2	0	2	These reports were originally handled within the full text exclusion workflow in Excel, but they are separated here for PRISMA reporting.
Reports assessed for eligibility	62	51	113	Reports retrieved and assessed against the full text eligibility criteria.
Reports excluded after full text assessment	27	24	51	This count excludes the 2 reports not retrieved and includes only reports assessed for eligibility.
Studies included from the primary database pathway	35	27	62	Studies that satisfied the full text criteria and were retained from Scopus and Web of Science.

Note. Wave 1 includes Run IDs S01a and S02a. Wave 2 includes Run IDs S01b, S01c, S02b and S02c.

Table 3.2 reports the full-text exclusion reasons for the primary database pathway.

Table 3.2. Full-text exclusion reasons for the primary database pathway

Exclusion reason	Count
E1 Not manufacturing or not industrial context	0
E2 Not relevant operational level	5
E3 No energy KPI or not computable	35
E4 Conceptual only	1
E5 Insufficient method detail	4
E6 Not discrete manufacturing	6
Total	**51**

Table 3.3 reports the detailed study selection counts for the supplementary Google Scholar pathway, including title screening, title and abstract screening, report retrieval and final inclusion.

Table 3.3. Detailed study selection counts for the supplementary Google Scholar pathway

Stage	Count	Run ID / source detail	Explanation
Records identified from Google Scholar	157	S03a = 78, S03b = 64, S03c = 15	Supplementary Google Scholar records retrieved across three targeted searches.
Duplicates removed before screening	61	S03a, S03b, S03c combined	Duplicate records were merged in Zotero before screening.
Records screened by title	96	After deduplication	Records remaining after deduplication and subjected to initial title screening.
Records excluded at title stage	49	Title screening	Records clearly outside the review scope or irrelevant to the thesis focus.
Records screened by title and abstract	47	Title-retained records	Records retained after title screening and carried forward to title and abstract screening.
Records included at title and abstract screening	17	Title and abstract screening	Records clearly meeting the title and abstract inclusion logic.
Records marked uncertain at title and abstract screening	6	Title and abstract screening	Records carried forward because eligibility could not be confirmed from title and abstract.
Records excluded at title and abstract screening	24	Title and abstract screening	Records excluded because they failed the predefined title and abstract criteria.
Reports sought for retrieval	23	Included and uncertain records	Included and uncertain records were carried forward for full-text retrieval.
Reports not retrieved	0	Google Scholar pathway	All reports sought for retrieval from Google Scholar were obtained.
Reports assessed for eligibility	23	Retrieved reports	Full-text reports assessed against the predefined eligibility criteria.
Reports excluded after full-text assessment	9	Full-text assessment	Reports excluded after full-text review using the predefined exclusion codes.
Studies included from the supplementary pathway	14	Google Scholar pathway	Studies retained from the Google Scholar pathway after full-text assessment.

Table 3.4 reports the full-text exclusion reasons for reports assessed in the supplementary Google Scholar pathway.

Table 3.4. Full-text exclusion reasons for the supplementary Google Scholar pathway

Exclusion reason	Count
E1 Not manufacturing or not industrial context	0
E2 Not relevant operational level	1
E3 No energy KPI or not computable	1
E4 Conceptual only	2
E5 Insufficient method detail	0
E6 Not discrete manufacturing	5
Total	**9**

Table 3.5 summarizes the final aggregation of included studies from the primary database pathway and the supplementary Google Scholar pathway.

Table 3.5. Final aggregation of included studies

Source pathway	Included studies
Primary databases (Scopus and Web of Science)	62
Supplementary Google Scholar pathway	14
Total studies included in the review	**76**

Explanatory note on the Google Scholar pathway

The Google Scholar pathway differed from the primary database pathway because abstracts were not consistently available and platform-level filtering for language and document type was limited. As a result, Google Scholar records were first subjected to **title screening** to remove clearly irrelevant records before proceeding to **title-and-abstract screening**. This title-stage triage did not replace the predefined title-and-abstract decision rules but rather served as an additional preliminary filter tailored to source-specific limitations. The retained subset then underwent title-and-abstract screening using the same general protocol logic as the primary pathway, followed by full-text assessment using the same predefined eligibility criteria.

Explanatory note on stage-specific screening logic

At title-and-abstract stage, a study was retained when the record indicated all of the following:

1. a discrete industrial manufacturing context.
2. an explicit energy focus, such as energy consumption, energy efficiency, energy management, KPI, or EnPI.

3. an energy-related method, monitoring logic, modelling or optimization context, or evidence of measured operational data.

Title and abstract screening removed clearly out of scope records and retained uncertain records for full text assessment. Final eligibility required enough detail to identify the indicator and operational boundary and required data and either a clear formula or sound computation logic. Papers failing these criteria were excluded with predefined exclusion codes.

Appendix 4. Selected Studies Included in the Final Review

Appendix 4 presents the studies included in the final review. Table 4.1 lists each selected study with its paper ID, title, publication year, and citation key. This table supports traceability between the final review dataset and the studies cited in the thesis.

Table 4.1. Selected studies included in the final review

Paper ID	Title	Publication Year	Citation key
P001	Smart Hybrid Maintenance as a Pathway to Energy-Efficient Manufacturing	2026	(Dudzik et al. 2026)
P022	A Power Disaggregation Approach for Fine-grained Machine Energy Monitoring by System Identification	2016	(Panten et al. 2016)
P023	Pattern recognition in load profiles of electric drives in manufacturing plants	2015	(Reger et al. 2015)
P029	STUDY ON THE LOAD PROFILE CHARACTERISTICS OF MACHINE TOOLS IN MACHINING OPERATIONS	2025	(Wächter et al. 2025)
P050	Energy Efficiency in Industry 4.0: The Case of Batch Production Processes	2020	(Nota et al. 2020)
P051	An energy-aware cyber physical system for energy Big data analysis and recessive production anomalies detection in discrete manufacturing workshops	2020	(Zhang et al. 2020)
P053	Big Data enabled Intelligent Immune System for energy efficient manufacturing management	2018	(Wang et al. 2018)
P055	Edge Computing Enabled Production Anomalies Detection and Energy-Efficient Production Decision Approach for Discrete Manufacturing Workshops	2020	(Zhang & Ji 2020)
P061	Cyber Physical System and Big Data enabled energy efficient machining optimization	2018	(Liang et al. 2018)
P062	FASTory assembly line power consumption data	2023	(Elahi et al. 2023)
P065	Multi-objective optimization of milling process: exploring trade-off among energy consumption, time consumption and surface roughness	2023	(Yang et al. 2023)
P066	A real time condition based sustainable maintenance method for milling process	2024	(Wu et al. 2024)
P067	An Internet of Things based energy efficiency monitoring and management system for machining workshop	2018	(Chen et al. 2018b)
P068	Infinitely repeated game based real-time scheduling for low-carbon flexible job shop considering multi-time periods	2020	(Wang et al. 2020)
P069	Resource scheduling based on energy consumption for sustainable manufacturing	2017	(Raileanu et al. 2017)
P070	Event-Driven Online Machine State Decision for Energy-Efficient Manufacturing System Based on Digital Twin Using Max-Plus Algebra	2019	(Wang et al. 2019b)
P072	Data Acquisition Network Configuration and Real-Time Energy Consumption Characteristic Analysis in Intelligent Workshops for Social Manufacturing	2022	(Zhang et al. 2022)
P074	Energy load profile analysis on machine level	2018	(Teiwes et al. 2018)
P076	Energy use analysis and local benchmarking of manufacturing lines	2017	(ElMaraghy et al. 2017)
P081	An energy modeling and evaluation approach for machine tools using generalized stochastic Petri Nets	2016	(Xie et al. 2016)

P082	Uncertainty reduction in measuring and verification of energy savings by statistical learning in manufacturing environments	2016	(Oses et al. 2016)
P083	IoT Solution for Energy Optimization in Industry 4.0: Issues of a Real-life Implementation	2018	(del Campo et al. 2018)
P086	Intelligent Immune System for Sustainable Manufacturing	2018	(Li & Cai 2018)
P089	Sensor network design for smart manufacturing - Application on precision machining	2020	(Awasthi & Bollas 2020)
P090	A MATERIAL-GENERAL ENERGY PREDICTION MODEL FOR MILLING MACHINE TOOLS	2016	(Budinoff et al. 2016)
P091	Artificial Neural Network Framework for Hybrid Control and Monitoring in Turning Operations	2025	(Abaza & Gheorghita 2025)
P093	A mechanism-data hybrid-driven modeling method for predicting machine tool-cutting energy consumption	2025	(Meng et al. 2025)
P099	An estimation methodology of energy consumption for the intelligent CNC machining using STEP-NC	2022	(Cheng et al. 2022)
P101	Simulation-based machine shop operations scheduling system for energy cost reduction	2017	(Kim et al. 2017)
P103	Development of a Transient Energy Prediction Model for Machine Tools	2021	(Pawanr et al. 2021)
P105	An Integrated Energy Data Analytics Approach for Machine Tools	2020	(Kang et al. 2020)
P109	A framework for energy monitoring of machining workshops based on IoT	2018	(Chen et al. 2018a)
P110	Ambient intelligence for optimal manufacturing and energy efficiency	2015	(Robinson et al. 2015)
P114	PLATFORM FOR MONITORING AND COMPARING MACHINING PROCESSES IN TERMS OF ENERGY EFFICIENCY	2019	(Haas et al. 2019)
P115	A Configurable On-Line Monitoring System Towards Energy Consumption of Machine Tools	2018	(Wu et al. 2018)
P118	Energy management in the formation of light, starter, and ignition lead-acid batteries	2019	(Cabello Eras et al. 2019)
P121	Application of Fuzzy TOPSIS and Harmonic Mitigation Measurement on Lean Six Sigma: A Case Study in Smart Factory	2023	(Duc et al. 2023)
P124	Predicting electrical power consumption of end milling using a virtual machining energy toolkit (V_MET)	2023	(Pantazis et al. 2023)
P131	Digital twin-driven carbon emission prediction and low-carbon control of intelligent manufacturing job-shop	2019	(Zhang & Ji 2019)
P133	Modelling of energy demand from computer numerical control (CNC) toolpaths	2017	(Edem & Mativenga 2017)
P136	Developing a virtual machining model to generate MTConnect machine-monitoring data from STEP-NC	2016	(Shin et al. 2016)
P138	Energy efficiency state identification in milling processes based on information reasoning and Hidden Markov Model	2018	(Cai et al. 2018)
P140	Data Driven Production Runtime Energy Control of Manufacturing Systems	2015	(Sun et al. 2015)
P142	Task Scheduling of Material-Handling Manipulator for Enhancing Energy Efficiency in Flow-Type FMS	2020	(Yonemoto et al. 2020)
P143	Feature-oriented energy consumption allowance approach of machining systems for energy-efficient manufacturing	2026	(Feng et al. 2026)
P146	Flexible process planning based on predictive models for machining time and energy consumption	2023	(Chu et al. 2023)
P148	Modeling and Assessment of Power Consumption for Green Machining Strategy	2023	(Won et al. 2023)
P152	A practical energy consumption prediction method for CNC machine tools: cases of its implementation	2018	(Shen et al. 2018)
P154	Energy-aware integration of process planning and scheduling of advanced machining workshop	2017	(Zhang et al. 2017)

P155	Holistic Context-Sensitivity for Run-Time Optimization of Flexible Manufacturing Systems	2017	(Scholze et al. 2017)
P156	Developing an energy-efficient process planning system for prismatic parts via STEP-NC	2019	(Wang et al. 2019a)
P169	Data-Driven Integration of Scheduling and Control With Closed-Loop Prediction for Industrial Flexible Production	2025	(Jiang et al. 2025)
P172	MILP models and effective heuristic for energy-aware parallel machine scheduling with shared manufacturing	2025	(Cheng et al. 2025)
P175	Optimization of thermal energy and logistics innovation in flexible manufacturing systems based on artificial intelligence: green supply chain management	2025	(Chen 2025)
P177	A Proactive Manufacturing Resources Assignment Method Based on Production Performance Prediction for the Smart Factory	2022	(Wang et al. 2022)
P179	Big data driven predictive production planning for energy-intensive manufacturing industries	2020	(Ma et al. 2020)
P193	A multi-objective differential evolution algorithm for parallel batch processing machine scheduling considering electricity consumption cost	2018	(Zhou et al. 2018)
P195	Energy-Efficient Job-Shop Dynamic Scheduling System Based on the Cyber-Physical Energy-Monitoring System	2018	(Feng et al. 2018)
P196	Perception data-driven optimization of manufacturing equipment service scheduling in sustainable manufacturing	2016	(Xu et al. 2016)
P200	Sustainable Process Planning for Customized Production Optimization	2016	(Wang et al. 2016)
P202	A Genetic Algorithm Optimizer For Dynamic Product Routing In Agile Manufacturing Environment	2018	(Ladosz et al. 2018)
P210	Optimizing Power Consumption in Robotized Job-Shop Manufacturing	2015	(Raileanu et al. 2015)
P215	Automatic assessment of machine tool energy efficiency and productivity	2017	(Hacksteiner et al. 2017)
P216	Energy Performance Indicator (EnPI) Prediction of a Compressed Air System in a Can Manufacturing Factory	2023	(Kadir et al. 2023)
P222	Hybrid virtual metering points–a low-cost, near real-time energy and resource flow monitoring approach for production machines without PLC data connection	2021	(Sossenheimer et al. 2021)
P227	Process monitoring for energy assessment of parts drying processes	2023	(Elserafi et al. 2023)
P228	The Synergy Between Maintenance and Energy Efficiency: Case Study of an Industrial Plant in Tangier	2022	(Chaibi et al. 2022)
P237	Real-time assessment of the overall effectiveness of legacy machine tools	2024	(Da Costa et al. 2024)
P240	Energy efficiency benchmarking methodology for mass and high-mix low-volume productions	2015	(Tan et al. 2015)
P246	Empirical modeling and simultaneous optimization of energy efficiency/demand, cost and productivity in incremental forming of metallic clad composite	2017	(Hussain & Al-Ghamdi 2017)
P252	A comparative study of rubber block properties produced by a novel rotary disc granulator and a conventional creper under different gap configurations	2026	(Tuljittraporn et al. 2026)
P261	Taguchi–Gray-Based Optimization of Hot Rough Rolling: Energy Efficiency and Dimensional Accuracy	2026	(Yilmaz et al. 2026)
P269	An analytical model for identifying and addressing energy efficiency improvement opportunities in industrial production systems–Model development and testing experiences from Sweden	2017	(Svensson & Paramonova 2017)
P299	Application of an energy management system to develop an energy planning in a pickling line	2017	(Escorcia et al. 2017)
P300	An Approach to Electricity Monitoring and Targeting (M&T) in Irish Precision Engineering SMEs	2016	(Cosgrove et al. 2016)
P302	An interactive resource value mapping tool to support the reduction of inefficiencies in smart manufacturing processes	2021	(Marconi et al. 2021)

Appendix 5. Detailed article-level information for the selected studies

Appendix 5 provides article-level information for the selected studies. Table 5.1 reports the main industry context and study type for each paper included in the final review. This table supports the classification of the review dataset and provides background information for the analysis in the thesis.

Table 5.1. Selected studies included in the final review

Paper ID	Main Industry Context	Study Type
P001	Cross-process studies	Method / framework
P022	Cross-process studies	Monitoring / measurement
P023	Cross-process studies	Modelling / optimization
P029	Machining / machine tools	Monitoring / measurement
P050	Other discrete manufacturing processes	Method / framework
P051	Cross-process studies	Modelling / optimization
P053	Method / framework development	Method / framework
P055	Cross-process studies	Modelling / optimization
P061	Machining / machine tools	Modelling / optimization
P062	Assembly / assembly lines	Monitoring / measurement
P065	Machining / machine tools	Modelling / optimization
P066	Machining / machine tools	Modelling / optimization
P067	Machining / machine tools	Method / framework
P068	Cross-process studies	Modelling / optimization
P069	Cross-process studies	Modelling / optimization
P070	Cross-process studies	Modelling / optimization
P072	Cross-process studies	Method / framework
P074	Machining / machine tools	Monitoring / measurement
P076	Cross-process studies	Monitoring / measurement
P081	Machining / machine tools	Modelling / optimization
P082	Cross-process studies	Modelling / optimization
P083	Method / framework development	Method / framework
P086	Method / framework development	Modelling / optimization
P089	Machining / machine tools	Monitoring / measurement
P090	Machining / machine tools	Modelling / optimization
P091	Machining / machine tools	Modelling / optimization
P093	Machining / machine tools	Modelling / optimization
P099	Machining / machine tools	Modelling / optimization
P101	Machining / machine tools	Modelling / optimization
P103	Machining / machine tools	Modelling / optimization
P105	Machining / machine tools	Monitoring / measurement
P109	Machining / machine tools	Method / framework
P110	Method / framework development	Method / framework
P114	Machining / machine tools	Monitoring / measurement
P115	Machining / machine tools	Monitoring / measurement
P118	Other discrete manufacturing processes	Case-based
P121	Cross-process studies	Modelling / optimization
P124	Machining / machine tools	Modelling / optimization
P131	Cross-process studies	Modelling / optimization
P133	Machining / machine tools	Modelling / optimization
P136	Machining / machine tools	Modelling / optimization
P138	Machining / machine tools	Modelling / optimization
P140	Cross-process studies	Modelling / optimization
P142	Cross-process studies	Modelling / optimization
P143	Machining / machine tools	Method / framework
P146	Machining / machine tools	Modelling / optimization
P148	Machining / machine tools	Modelling / optimization
P152	Machining / machine tools	Modelling / optimization
P154	Machining / machine tools	Modelling / optimization

P155	Cross-process studies	Method / framework
P156	Machining / machine tools	Method / framework
P169	Assembly / assembly lines	Modelling / optimization
P172	Cross-process studies	Modelling / optimization
P175	Cross-process studies	Method / framework
P177	Cross-process studies	Modelling / optimization
P179	Cross-process studies	Modelling / optimization
P193	Cross-process studies	Modelling / optimization
P195	Cross-process studies	Modelling / optimization
P196	Cross-process studies	Modelling / optimization
P200	Machining / machine tools	Method / framework
P202	Cross-process studies	Modelling / optimization
P210	Cross-process studies	Modelling / optimization
P215	Machining / machine tools	Monitoring / measurement
P216	Other discrete manufacturing processes	Modelling / optimization
P222	Cross-process studies	Monitoring / measurement
P227	Surface treatment / finishing processes	Monitoring / measurement
P228	Cross-process studies	Case-based
P237	Machining / machine tools	Monitoring / measurement
P240	Cross-process studies	Method / framework
P246	Forming / rolling / metal shaping	Modelling / optimization
P252	Surface treatment / finishing processes	Case-based
P261	Forming / rolling / metal shaping	Modelling / optimization
P269	Cross-process studies	Method / framework
P299	Surface treatment / finishing processes	Case-based
P300	Cross-process studies	Monitoring / measurement
P302	Cross-process studies	Method / framework

Appendix 6. KPI-level Traceability Table Excerpt

Appendix 6 presents an excerpt from the KPI-level traceability table used in this thesis. Table 6.1 shows selected KPI entries and coding fields used for taxonomy assignment and framework use. The included fields cover paper ID, standardized KPI name, unit, energy KPI status, KPI type, process or industry context, framework role, formula availability, mapping summary, and intended use.

Table 6.1. KPI entries used for taxonomy assignment

Paper ID	KPI standardized name	Unit	Energy KPI status	KPI type	Process / Industry Context	Framework role	Formula availability	Mapping summery	Intended use
P001	Energy efficiency indicator	Not reported	Direct energy KPI/EnPI	Energy efficiency ratio	Cross-process studies	Decision-layer KPI	Calculation logic inferable	No selected-standard mapping	Assessment of machine energy performance and support for predictive-maintenance decision-making
P001	Specific energy consumption	Not reported	Direct energy KPI/EnPI	Specific / intensity-based energy KPI	Cross-process studies	Decision-layer KPI	Weak or incomplete calculation basis	No selected-standard mapping	Assessment of production energy intensity and comparison before/after predictive maintenance
P001	Overall equipment effectiveness	Not reported	Energy-related supporting KPI	Composite / hybrid KPI	Cross-process studies	Supporting KPI	Explicit formula reported	No selected-standard mapping	Operational performance assessment and supporting analysis of energy-aware predictive maintenance
P022	Aggregate machine power demand	kW	Direct energy KPI/EnPI	Power / demand KPI	Cross-process studies	Measurement-enabling KPI	Calculation logic inferable	No selected-standard mapping	Machine-level energy monitoring; basis for power disaggregation
P022	Machine component power demand	kW	Direct energy KPI/EnPI	Power / demand KPI	Cross-process studies	Measurement-enabling KPI	Calculation logic inferable	No selected-standard mapping	Fine-grained component-level energy monitoring and energy transparency
P022	Machine component energy consumption	Not reported	Direct energy KPI/EnPI	Absolute energy consumption	Cross-process studies	Measurement-enabling KPI	Weak or incomplete calculation basis	No selected-standard mapping	Component-level energy monitoring and energy transparency
P023	Electric drive active power profile	kW	Direct energy KPI/EnPI	Power / demand KPI	Cross-process studies	Measurement-enabling KPI	Calculation logic inferable	No selected-standard mapping	Automated classification of load profiles; segmentation of operations; basis for

									automated KPI generation
P023	Specific energy consumption	Not reported	Direct energy KPI/EnPI	Specific / intensity-based energy KPI	Cross-process studies	Decision-layer KPI	Calculation logic inferable	No selected-standard mapping	Automated calculation of part-level energy attributes and KPI generation
P029	Machine electrical load profile	kW	Direct energy KPI/EnPI	Power / demand KPI	Machining / machine tools	Measurement-enabling KPI	Calculation logic inferable	No selected-standard mapping	Continuous energy monitoring; load-profile analysis; basis for pattern/cycle characterization
P029	Average power demand	kW	Direct energy KPI/EnPI	Power / demand KPI	Machining / machine tools	Decision-layer KPI	Calculation logic inferable	No selected-standard mapping	Characterization and comparison of machining-cycle load behavior; statistical description of machine-tool power demand
P029	Maximum power demand	kW	Direct energy KPI/EnPI	Power / demand KPI	Machining / machine tools	Decision-layer KPI	Calculation logic inferable	No selected-standard mapping	Characterization of peak loads during machining cycles; comparison of load behavior
P029	Minimum power demand	kW	Direct energy KPI/EnPI	Power / demand KPI	Machining / machine tools	Decision-layer KPI	Calculation logic inferable	No selected-standard mapping	Load-profile characterization; comparison of lower bound and negative peak behavior
P029	Median power demand	kW	Direct energy KPI/EnPI	Power / demand KPI	Machining / machine tools	Decision-layer KPI	Calculation logic inferable	No selected-standard mapping	Robust statistical characterization of machining-cycle power demand

Appendix 7. Excerpts from Level-based KPI Selection Tables

Appendix 7 presents excerpts from the level-based KPI selection tables used in the decision framework. Tables 7.1-7.5 show selected KPI entries for line or cell level, machine level, process or unit-operation level, multi-level entries, and entries that are not level-specific or weakly specified. These excerpts illustrate the level-based selection logic used to connect KPI entries with operational manufacturing levels and input requirement.

Table 7.1. Line or cell-level KPI selection table used in the decision framework

KPI standardized name	Boundary	Data type group	Input requirement group	Required inputs	KPI type
Impact variation of energy consumption (DI)	Production line	Derived and indirect data	Energy plus production output	Theoretical environmental impact (Ith); actual impact (Iact); production-volume context	Composite / hybrid KPI
Energy loss due to type change	Production line	Aggregated and summarized data	Energy plus time/state	W0 (standby power); W1 (average power to support); W2 (average power in use); tend prod; tchange prep; teff change; tstart prep; tstart; ttype change	Absolute energy consumption
Energy loss due to plant failure	Production line	Aggregated and summarized data	Energy plus time/state	W0; W1; W2; tend prod; tprep maint; teff maint; tstart prep; tstart	Absolute energy consumption
Energy loss due to start-up and shut-down transients	Production line	Aggregated and summarized data	Energy plus time/state	W0; W1; W2; tsd; tsu	Absolute energy consumption
Energy loss due to micro-stops	Production line	Aggregated and summarized data	Energy plus time/state	W0; W1; W2; tend prod; tprep maint; teff maint; tstart prep; tstart	Absolute energy consumption
Energy loss due to slowdowns	Production line	Aggregated and summarized data	Energy plus time/state	W0; W1; W2; tslowdown	Absolute energy consumption
Energy loss due to waste	Production line	Aggregated and summarized data	Energy plus production output	W0; W1; W2; ql (quality-loss time)	Absolute energy consumption
Overall equipment effectiveness	Production line	Derived and indirect data	Non-energy contextual input	Availability; Performance; Quality; production-loss data	Composite / hybrid KPI
Total energy consumption	Production line	Derived and indirect data	Energy plus time/state	Etotal(Mi) for all machines	Absolute energy consumption
Material removal energy utilization ratio of machining task	Multi-machine system	Derived and indirect data	Energy plus time/state	Material removal energy consumption of all operations; standby, air-cutting, and cutting energy consumption of all operations in the machining task	Energy efficiency ratio
Specific energy consumption of machining task	Multi-machine system	Derived and indirect data	Energy plus production output	Standby, air-cutting, and cutting energy consumption summed across all operations of the task; task quantity N	Specific / intensity-based energy KPI
Makespan	Multi-machine system	Derived and indirect data	Non-energy contextual input	End time of the last scheduled operation; schedule of all operations	Time-based energy KPI

Table 7.2. Machine level KPI selection table used in the decision framework

KPI standardized name	Boundary	Data type group	Input requirement group	Required inputs	KPI type
Energy efficiency indicator	Machine-level system	Derived and indirect data	Energy plus production output	Energy input; useful output; operational process data	Energy efficiency ratio
Specific energy consumption	Machine-level system	Derived and indirect data	Energy plus production output	Energy consumption; production/output denominator	Specific / intensity-based energy KPI
Overall equipment effectiveness	Machine-level system	Derived and indirect data	Non-energy contextual input	Availability; Performance; Quality; operational status/downtime data; process performance and quality information	Composite / hybrid KPI
Aggregate machine power demand	Machine-level system	Time-resolved measured data	Energy or power only	Aggregate power measurement	Power / demand KPI
Machine component power demand	Machine subsystem	Time-resolved measured data	Energy plus process parameters	Aggregate power data; component control signals; PLC data; OPC-UA data	Power / demand KPI
Machine component energy consumption	Machine subsystem	Time-resolved measured data	Energy plus process parameters	Aggregate energy/power data; component control signals; machine operational data	Absolute energy consumption
Electric drive active power profile	Machine subsystem	Time-resolved measured data	Energy plus time/state	Active power measurements of the spindle drive / electric drives; sampled load profile; training pattern profiles	Power / demand KPI
Specific energy consumption	Machine-level system	Derived and indirect data	Energy plus production output	Detected start and end points of each part; active power profile; recognized patterns; part-level energy/use data derived from the segmented profile	Specific / intensity-based energy KPI
Machine electrical load profile	Machine-level system	Time-resolved measured data	Energy plus time/state	Power measured at the mains connection point of the machine; sampled time series; machining-cycle segmentation	Power / demand KPI
Average power demand	Machine-level system	Derived and indirect data	Energy plus time/state	Power time series for identical machining patterns/cycles	Power / demand KPI
Maximum power demand	Machine-level system	Derived and indirect data	Energy plus time/state	Power time series for identical machining patterns/cycles	Power / demand KPI
Minimum power demand	Machine-level system	Derived and indirect data	Energy plus time/state	Power time series for identical machining patterns/cycles	Power / demand KPI
Median power demand	Machine-level system	Derived and indirect data	Energy plus time/state	Power time series for identical machining patterns/cycles	Power / demand KPI
Standard deviation of power demand	Machine-level system	Derived and indirect data	Energy plus time/state	Power time series for identical machining patterns/cycles	Power / demand KPI
Coefficient of variation of power demand	Machine-level system	Derived and indirect data	Energy or power only	Pc,std; Pc,avg	Composite / hybrid KPI
Energy efficiency (EF)	Machine-level system	Derived and indirect data	Energy plus process parameters	MEk (material removal energy consumption); AEk (auxiliary energy consumption)	Energy efficiency ratio
Processing energy efficiency (PEF)	Machine-level system	Derived and indirect data	Energy plus production output	V (material removal volume); MEk; AEk	Specific / intensity-based energy KPI

Table 7.3. Process or unit-operation KPI selection table used in the decision framework.

KPI standardized name	Boundary	Data type group	Input requirement group	Required inputs	KPI type
Standby energy consumption	Process step	Derived and indirect data	Energy plus time/state	Partitioned process energy data; clustered state-wise energy data; sampling interval	Absolute energy consumption
Idle energy consumption	Process step	Derived and indirect data	Energy plus time/state	Partitioned process energy data; clustered state-wise energy data; sampling interval	Absolute energy consumption
Air-cutting energy consumption	Process step	Derived and indirect data	Energy plus time/state	Partitioned process energy data; clustered state-wise energy data; sampling interval	Absolute energy consumption
Cutting energy consumption	Process step	Derived and indirect data	Energy plus time/state	Partitioned process energy data; clustered state-wise energy data; sampling interval	Absolute energy consumption
Maximum state energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of state Xi (xij values)	Power / demand KPI
Mean state energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of state Xi (xij values); Ni observations	Power / demand KPI
Standard deviation of state energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of state Xi (xij values); Meani; Ni observations	Composite / hybrid KPI
The energy consumption of Machine Mi during machining	Individual machine	Derived and indirect data	Energy plus production output	Aij; E_machining(Mi,Jj); component-machine assignment	Absolute energy consumption
The energy consumption of Machine Mi during waiting	Individual machine	Derived and indirect data	Energy plus time/state	Total energy consumption of machine Mi; machining energy consumption of machine Mi	Absolute energy consumption
Mean Absolute Percentage Error	Process step	Derived and indirect data	Energy plus time/state	Measured energy pattern; standard energy pattern; aligned pattern length N	Composite / hybrid KPI
Standby energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of standby state for each workpiece/process	Absolute energy consumption
Idle energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of idle state for each workpiece/process	Absolute energy consumption
Air-cutting energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of air-cutting state for each workpiece/process	Absolute energy consumption
Cutting energy consumption	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data of cutting state for each workpiece/process	Absolute energy consumption
Maximum energy consumption of state i	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data set p_i^t for machining state i	Power / demand KPI
Minimum energy consumption of state i	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data set p_i^t for machining state i	Power / demand KPI
Mean energy consumption of state i	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data set p_i^t; N_i^t observations	Power / demand KPI
Standard deviation of energy consumption of state i	Process step	Derived and indirect data	Energy plus time/state	Energy consumption data set p_i^t; Mean_i^t; N_i^t observations	Composite / hybrid KPI

Table 7.4. Multi-level KPI selection table used in the decision framework.

KPI standardized name	Boundary	Data type group	Input requirement group	Required inputs	KPI type
Machine tool energy utilization ratio of machining workshop	Multi-machine system	Derived and indirect data	Energy plus resource/environmental data	Total energy consumption of all machine tools; total energy consumption of all auxiliary equipment	Energy efficiency ratio
Cutting energy utilization ratio of machining workshop	Multi-machine system	Derived and indirect data	Energy plus time/state	Total cutting energy consumption of all machine tools; total energy consumption of all machine tools	Energy efficiency ratio

Table 7.5. Not level-specific and weakly specified KPI entries used with caution in the decision framework.

KPI standardized name	Boundary	Data type group	Input requirement group	Required inputs	KPI type
Battery capacity coefficient	Unit operation	Derived and indirect data	Non-energy contextual input	Battery capacity Cb; smallest battery capacity Cbmin	Not clear / other
Scale coefficient for allowance	Multi-level	Derived and indirect data	Non-energy contextual input	Service time of CNC machine tools	Not clear / other
Geometry factor	Not reported	Derived and indirect data	Non-energy contextual input	Part geometric feature; blind-hole radius r; blind-hole depth d; feature class	Composite / hybrid KPI