Fontoura, L., de Mattos Nascimento, D., Neto, J.V., Garcia-Buendia, N., Garza-Rayes, J.A., Lima, G.B.A, Tortorella, G.L., Caiado, R.G.G., and Meiriño, M.J. (2023), “Real-time energy flow mapping: A VSM-based proposal for energy efficiency”, *Journal of Cleaner Production*, Vol. 419, 137871, doi: https://doi.org/10.1016/j.jclepro.2023.137871.

Real-time Energy Flow Mapping: a VSM-based proposal for energy efficiency

Rising energy costs and the current concern about sustainability issues directly impact the competitiveness and survival of organizations, promoting the search for continuous improvement in industrial production processes. The present study, by identifying the absence in the literature of models based on Value Stream Mapping and integrated with Industry 4.0 technologies that promote better energy efficiency practices in industrial processes, proposes a new Lean Management model called Real-time Energy Flow Mapping. This innovative model, provide capabilities to a visual, digital and sustainable management system of all energy behavior in machines and equipment using fully parameterizable metrics and rules. Also, estimulating stakeholders with the ability to predict and monitor energy costs, as well as identify possible problems due to changes in the behavior of energy consumption in machines, thus helping managers to make decisions faster and more dynamically. As a result, the literature search turned up 17 Value Stream Mapping based models with a focus on energy efficiency, along with 31 metrics grouped on energy, environmental and production processes. After discussions by the Focus Groups, 16 resulting metrics were submitted to expert panel, in which the least relevant were discarded and the 13 most relevant classified using Fuzzy Delphi. An analysis to verify the interrelationships between the metrics is performed using the Fuzzy DEMATEL, being finally applied in the proposed model. A case study of the model was carried out, submitting it operationally at the LabFaber 4.0, empirically validating the study. The Real-time Energy Flow Mapping fills the gap in the literature on Value Stream Mapping models to improve energy efficiency, monitoring energy consumption through dynamic mapping of the energy flow of production processes, identifying the area with increased potential for energy savings through changes in operating behavior that reduce overall energy consumption and environmental impacts.

Keywords: Lean Management; Value Stream Mapping; Industry 4.0; Energy efficiency; Delphi Study; Fuzzy logic

Abbreviation	
BDA	Big-Data Analytics
CO	Carbon Monoxide
CO2	Carbon Dioxide
CPS	Cyber-Physical-Systems
DVSM	Dynamic Value Stream Mapping
ESG	Environmental, Social and Corporate Governance
EVSM	Energy Value Stream Mapping

H2S	Hydrogen Sulfide
I4.0	Industry 4.0
IEVA	Integrated Energy Value Analysis
IoT	Internet of Things
IPS	Interpretive Structural Modelling
IT	Information Technology
LCAVSM	Life Cycle assessment Value Stream Mapping
LM	Lean Management
MFCA	Material Flow Cost Accounting
NH3	Ammonia
NO2	Nitrogen Dioxide
OT	Operational Technology
RQ	Research Question
RTEFM	Real-time Energy Flow Mapping
SO2	Sulfur Dioxide
SVSM	Sustainable Value Stream Mapping
TFN	Triangular Fuzzy Numbers
TVSM	Therblig-embedded VSM
VSM	Value Stream Mapping
VVLD	Value-Value Load Diagram
WoS	Web of Science

1. Introduction

The 1973 oil crisis triggered the realisation that energy raw materials are exhaustible and will become increasingly scarce over time (Ates & Durakbasa, 2012). With the globalisation that integrated nations into a world economic system (Chen et al., 2019), the development of countries' economies has been mirrored by an increase in energy demands (X. D. Wu et al., 2019), culminating in an over five-fold increase in worldwide electricity consumption in just under 50 years (IEA, 2021b). Consequently, ongoing global concerns around energy consumption and climate change and the quest for more efficient energy use and management have led to the concept of sustainable development becoming consolidated in various countries (Bazurto et al., 2017). In addition to the concerns around efficient energy use, this concept also considers the cost of electricity (Akbaba, 1999), which has constantly increased in multiple countries worldwide (Adenuga et al., 2019).

The industrial sector is responsible for approximately 37% of global energy consumption (IEA, 2020) and 23% of CO2 emissions (IEA, 2021a). Economic crises and the strong competitive environment have prompted organisations to seek better commercial and strategic opportunities to boost their profits and market share (Valamede & Akkari, 2020). In this context, as energy-related issues are extremely important for companies in the industrial sector, energy-efficient production processes can guarantee a firm a market competitive advantage. The competitive and dynamic environment that companies are immersed in requires their constant adaption, with new practices, to meet market needs, while also keeping their processes sustainable (A.-Y. Chang & Cheng, 2019). An energy management system to improve energy efficiency provides an organisation with guidelines to establish energy policies, execute efficient audits, calculate consumption trends and estimate and compare energy data, as well as support for decision-making (Adenuga et al., 2019).

Evidence suggests that Lean Management (LM) tools help organisations achieve better operational performance by fulfilling the key requirements of profitability, quality and customer satisfaction (J A Garza-Reyes et al., 2018). LM practices used in organisational management include Just in Time (JIT), Total Productive Maintenance (TPM), Jidoka, Value Stream Mapping (VSM) (Andreadis et al., 2017), Kanban and Kaizen (Keskin et al., 2012). According to data from a survey of specialists, one of the most popular practical tools is VSM with 74.3% preference (J A Garza-Reyes et al., 2018). VSM is a lean tool based on visual presentation used to illustrate, identify and measure the waste generated by inefficient processes (Abdulmalek & Rajgopal, 2007). VSM has previously been used to address energy efficiency focusing on energy consumption (Sihag & Sangwan, 2019) and CO2 emissions (Heravi et al., 2020), life-cycle assessment (Estrada-Gonzalez et al., 2020), carbon efficiency and carbon emissions (Zhu et al., 2020) and energy waste (Jia et al., 2017), among others.

The fourth industrial revolution (I4.0) is envisaged as the fusion of information technology (IT) and operational technology (OT) (Ferreira et al., 2022) and focuses on the end-to-end digitisation and integration of digital industrial ecosystems, mainly Cyber-Physical-Systems (CPS), Internet of Things (IoT) and Cloud Computing technologies (Xu et al., 2018). The emergence of I4.0 in parallel with the digital transformation has made the technologies used in industrial production systems increasingly smarter (Schumacher et al., 2020), which creates a major challenge to the identification and implementation of strategic methods and the use of lean tools (Dombrowski & Mielke, 2015). I4.0 and LM are interrelated and I4.0 can enhance LM practices (Schumacher et al., 2020). The VSM approach has previously been studied in combination with I4.0 technologies focused on the circular economy (Nascimento et al., 2022), a human-centred approach (Wang et al., 2022), manufacturing (Huang et al., 2019a), healthcare operations (Tortorella et al., 2022), connectivity and information exchange (Nounou et al., 2022) and productivity enhancement (Tripathi et al., 2021), among others.

As can be observed, several works have addressed the use of VSM for assessing energy efficiency issues (Cosgrove et al., 2018) or used a LM perspective in combination with I4.0 technologies (Pagliosa et al., 2021). Traditional VSM neglected sustainability aspects as no energy indicators or metrics were included (Phuong & Guidat, 2018). The lack of models based on the VSM with a greater focus on sustainability (J. K. Y. Lee et al., 2021) has led to the need to carry out more advanced studies on the sustainable digital VSM topic (Jamil et al., 2020; Sulaiman et al., 2019). As it did not reflect the dynamic changes that occurred in production (Balaji et al., 2020), it needed to be integrated with technologies capable of obtaining data in real-time (Huang et al., 2019a). This research seeks to investigate the following research questions (RQs):

RQ1. How can a LM model integrated with energy, environmental and production process metrics improve energy efficiency in industries?

RQ2. What are the most relevant energy, environmental and production process metrics that can be integrated into an energy management model?

RQ3. What interrelationships exist between energy metrics on environmental and production process metrics?

The present study proposes and apply a VSM-based model named Real-time Energy Flow Mapping (RTEFM) that integrates energy, environmental and production process metrics, and I4.0 technologies to automatically and dynamically collect, map and model the energy flow in an industrial production process to address the above-mentioned issues. From a theoretical perspective, this work contributes to advancing knowledge on the implications of LM practices for sustainability issues such as energy efficiency and the advantages of I4.0 technologies. In practical terms, managers can adapt the proposed tool to the unique features of their production systems and validate it to improve energy efficiency control, failure analysis, energy contracting budget forecasting and decision-making through an aggregated visual approach.

This research contributes to methodology by concisely integrating and applying several research methods. Starting with a qualitative analysis to better understand industries' energy efficiency issues and needs, it develops a new energy management model through a scoping review and focus group discussions among specialists. The study subsequently uses Fuzzy Delphi and Fuzzy DEMATEL to quantitatively analyse the results to identify the most relevant energy, environmental and production process metrics and their strongest interrelationships. Finally, a case study using the model is applied in a real company, LabFaber 4.0, to empirically test and validate its operation.

This document is organised as follows. This section seeks to contextualise and introduce the research needs, gaps, questions and motivations. Section 2 presents a summarised background to the models found in the literature and the barriers to their implementation. Section 3 explains the four-step methodology used in detail: scoping review, focus groups, questionnaire design, two-round Delphi study using the Fuzzy Delphi and Fuzzy DEMATEL techniques, and case study. Section 4 presents the main study results following the structure of the RQs and the proposed conceptual model, while Section 5 discusses the main research findings. Section 6 summarises the study and offers some conclusions.

2. Background

As a result of constant energy shortages and rising prices for energy supplied, improving energy efficiency in equipment contained in industrial processes has become one of the ways to increase the company's profits and reduce the emission of greenhouse gases. According to Johansson and Thollander (2018), issues related to energy efficiency are not something optional for companies, but extremely important for their survival, directly reflecting on the final price of the product. The LM concept aims to ensure the company's development and survival, being a business strategy focused on working with minimum resources to achieve total quality (Valamede & Akkari, 2020). VSM, also known as material and information flow mapping, is a Lean tool used to analyse, examine, and evaluate specific work processes in a manufacturing operation (Verma & Sharma, 2019), being used to map the flow of the current process, helping specialists to identify areas where improvements may occur (Buer et al., 2018). As shown in Figure 1, flow mapping is one of the most popular Lean tools (Thanki & Thakkar, 2016) and is considered one of the most efficient ways to obtain data from production processes (Camgoz-Akdag et al., 2018).

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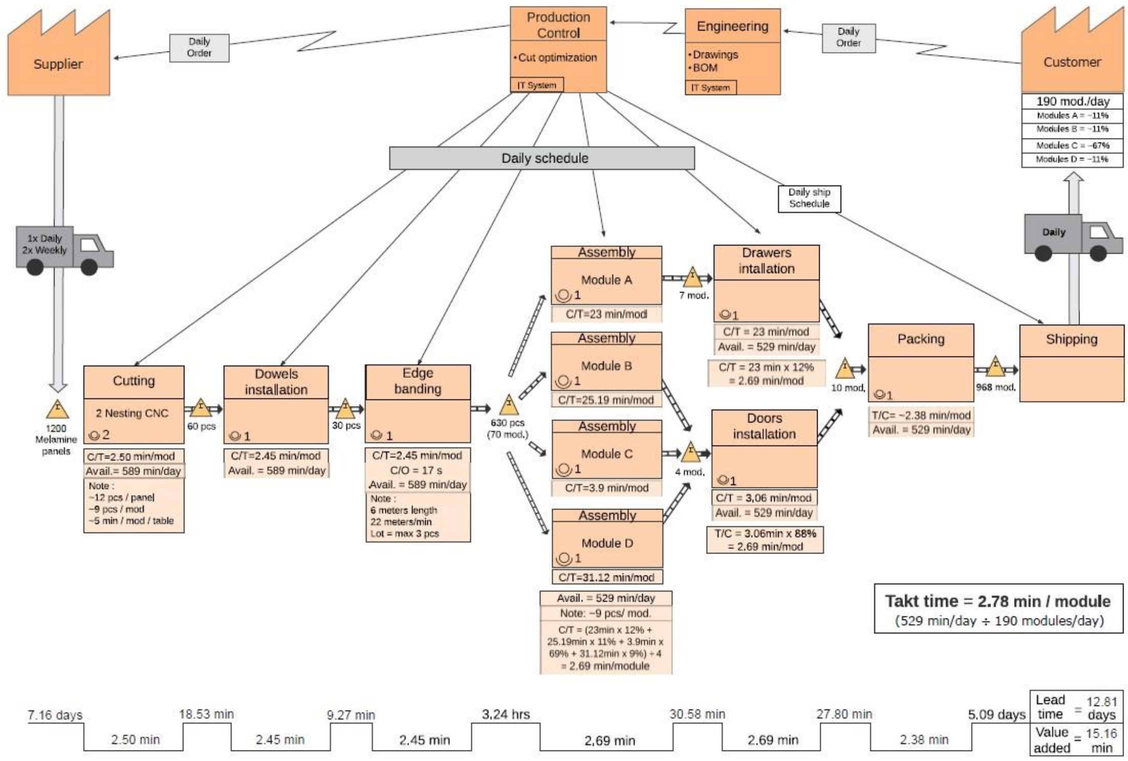

Figure 1. Example of a VSM applied to a production line (Ferreira et al., 2022)

Figure 1 shows an example of a VSM applied in a production line, from the entry of raw materials to the supply of final products to distributors, mapping material and information flow. The traditional VSM is a static tool (Balaji et al., 2020) and changes in the production line or products can directly impact the flow mapping, making updating it a constant challenge for specialists (Buer et al., 2018), therefore, integration with I4.0 technologies can improve the VSM by collecting data and process information in real time, making the tool more dynamic (Meudt et al., 2017). There are several technologies that are part of I4.0, as well as different understandings about which technologies are part of this concept. I4.0 is supported by nine technological pillars: Big-Data, Autonomous Industrial Robots, Simulation, Horizontal and Vertical Integration of Systems, IoT, Cyber-Security, Cloud Computing, Additive Manufacturing, and Augmented Reality (Pereira & Simonetto, 2018). In addition to these I4.0 technologies, Blockchain can be highlighted, which today is the most critical and vital emerging computer technology to achieve energy efficiency in buildings. Whose three main factors that made Blockchain an essential computer technology are real-time execution, security and transparency, followed by traceability and localized control (Qarnain et al., 2021).

In the literature, the year 2022 is characterized by a widespread energy crisis, which leads to a constant increase in electricity prices worldwide (Saligkaras & Papageorgiou, 2022). This global energy crisis stems from the Russian-Ukrainian conflict and has raised the prospect of returning to some sources of electricity that are far from being green and ecologically correct, thus forcing industries to adopt immediately new initiatives to reduce energy consumption (Borowski, 2022) as much as possible (Saktiawan et al., 2022). Futhermore, the lack of sustainability-oriented studies regarding VSM (J. K. Y. Lee et al., 2021), together with the lack of research on the integration and systematization of available knowledge about VSM (Gholami et al., 2019), has led to a growing number of professionals and researchers to propose the need to carry out more advanced studies concerning the sustainability-oriented VSM (Jamil et al., 2020; Sulaiman et al., 2019), given the difficulties in analyzing all relevant data from different products, as well as the complexity of verifying essential information related to environmental and production processes issues in a single VSM (J. K. Y. Lee et al., 2021). Added to this lack of studies, no previous studies have integrated energy efficiency and I4.0 technologies into a VSM-based approach to address dynamic changes and complex energy and production flow in manufacturing processes. Similarly, no previous studies have been identified that tried to understand which metrics would be the most relevant for better energy management and production processes or what their main interrelationships would be.

2.1 VSM-Based models found in literature

Several models analysed in the study were found during the scoping review, as shown in Table 1. Some of these only addressed integration with I4.0 technologies and others only the application of energy, environmental and production process metrics. In none of the studied models was VSM extended to energy management and integrated with I4.0 technology to provide dynamic data collection and analysis in real-time, enabling the modeling of energy through time series in order to allow better energy management, reduction of equipment failures, and budget forecast related to energy purchase.

Table 1. VSM-Based models found in literature

Models	Authors
VSM and Industry 4.0	
Dynamic VSM (DVSM)	Tran, Ruppert and Abonyi (2021); Abideen and Mohamad (2021); Balaji et al. (2020); Ramadan et al. (2020); Pasi, Mahajan and Rane (2020); Huang et al. (2019); Benzi, Clava and Bassi (2018); Wagner, Herrmann and Thiede (2018)
VSM4.0	Pagliosa, Tortorella and Ferreira (2021); Ilangakoon et al. (2021); Valamede and Akkari (2020); Fortuny-Santos et al. (2020); Buer, Strandhagen and Chan (2018); Mayr et al. (2018); Camgoz-Akdag, Beldek and Konyalioglu (2018)
VSM-Based Logistics 4.0	Boonsothonsatit, Tonchiangsai and Choowitsakunlert (2020)
Sustainable VSM (SVSM)	Phuong and Guidat (2018)
VSM and Energy Efficiency	
Energy VSM (EVSM)	Baysan et al. (2019); Verma & Sharma (2019); Cosgrove et al. (2018); Garza-Reyes et al. (2018); Melsas & Rosin (2018); Xie et al. (2018); Svensson & Paramonova (2017); Schönemann et al. (2016); Muller et al. (2014); Müller et al. (2014); Keskin et al. (2012)
Integrated Energy Value Analysis (IEVA)	Bettoni et al. (2015)
Therblig-embedded VSM (TVSM)	Sihag & Sangwan (2019); Jia et al. (2017)
Green VSM (GVSM)	Rukmayadi et al. (2016)
Value-Value Load Diagram (VVLD)	Thanki & Thakkar (2016)
Life Cycle assessment VSM (LCAVSM)	Estrada-Gonzalez et al. (2020)

2.1.1 VSM-Based models integrated with I4.0 technologies

The models that addressed the integration of VSM with I4.0 technologies presented as the integration of digital information in real-time to VSM, being able to identify any waste in the productive operation (Benzi et al., 2018), in addition to improving the analysis and visualization of processes (Huang et al., 2019b), thereby providing greater accuracy compared to traditional tools (Balaji et al., 2020), minimization of manufacturing lead times (Ramadan et al., 2020) and ability to monitor the positions of objects within the factory (Tran et al., 2021).

DVSM is a traditional VSM integrated with I4.0 technologies (Benzi et al., 2018) to obtain diagnostic information in real-time (Balaji et al., 2020), capable of storing, analysing, visualizing (Huang et al., 2019a), and minimize the downtime of the processes (Ramadan et al., 2020), focusing mainly on material tracking (Tran et al., 2021) and information flow in real-time (Wagner et al., 2018). VSM4.0 is a holistic integration of I4.0 technologies with VSM (Valamede & Akkari, 2020), in order to improve the service quality, prioritizing the solution of the main problems in the process (Camgoz-Akdag et al., 2018), not necessarily in real-time. SVSM is a VSM-Based data tracking model integrated with IoT with the purpose of reducing the time spent searching for materials in the process by workers (Phuong & Guidat, 2018). VSM-Based Logistics 4.0 integrate VSM and IoT to eliminate the gaps between the current-sate and future-state maps of logistics activities (Boonsothonsatit et al., 2020).

Although all models found with integration of I4.0 technologies presented innovations, none of them advanced with studies for the use of such resources for better energy management, focusing on the monitoring and flow of the production process and location of materials, not being able to really promote better energy efficiency practices. Several barriers to implementing these management models were detected in the scoping review, such as the need for technical knowledge for their implementation, use and maintenance (Balaji et al., 2020), high investment costs, lack of qualified professionals (Pagliosa et al., 2021), their application in real production conditions (Huang et al., 2019a), cultural issues (Pasi et al., 2020), resource limitations (Ilangakoon et al., 2021), legal, social and financial impacts (Mayr et al., 2018) and production problems (Wagner et al., 2018).

2.1.2 VSM-Based models focused on energy efficiency

The VSM-Based models that addressed the application of energy, environmental and production process metrics sought to address energy issues with traditional VSM. The main objective was to improve energy efficiency in companies by identifying the level of energy consumed (Keskin et al., 2012) and to reduce this significantly (Muller et al., 2014) by identifying the added and non-added energy values in the process cycles (Müller et al., 2014) to improve management practices (Svensson & Paramonova, 2017). These models can be used both as a diagnostic and a tool to help with energy budgeting (Verma & Sharma, 2019) by identifying the largest sources of waste (Baysan et al., 2019).

EVSM is a VSM-Based model integrated with energy metrics capable of detecting non-value-added energy consumption (Keskin et al., 2012), energy wastes (Muller et al., 2014), energy demands (Schönemann et al., 2016), energy savings (Melsas & Rosin, 2017), energy consumption (Xie et al., 2018), overload and variability effects on energy consumption (Baysan et al., 2019), value-added energy consumption, energy budgeting and economy savings (Verma & Sharma, 2019), allowing the identification of the area with the greatest potential of savings through changes in operational behaviour (Cosgrove et al., 2018).

IEVA integrate EVSM with energy audits and energy balance charts, enabling a top-down approach (Bettoni et al., 2015), TVSM is a model that integrated VSM with Therblig (Sihag & Sangwan, 2019) to improve energy transparency and the reduction of energy wastes of the process (Jia et al., 2017), GVSM is integrated with with Interpretive Structural Modelling (IPS) and Fuzzy AHP to improve sustainable logistics business and social activities (Rukmayadi et al., 2016), VVLD is a model that integrated VSM, Material Flow Cost Accounting (MFCA), and Pinch Analysis to measure the efficiency of use of production resources (Thanki & Thakkar, 2016), LCAVSM is eco-efficiency scheme based on integration of the Life Cycle Assessment (LCA) with VSM, focusing on energy use in order to reduce environmental impacts (Estrada-Gonzalez et al., 2020).

While the models presented are concerned with integrating energy metrics into the VSM for better process energy management, they did not propose a model with satisfactory integration with I4.0 technologies in order to meet all the current dynamics of the processes present in the productive processes, in view of the constant changes in production processes. Without this integration, new analyzes or even the fidelity of what was verified is limited to when the collections took place. Some barriers can be highlighted, such as the lack of integration with I4.0 technologies, which prevents real-time data collection, data analysis and storage and access to information. Some of the information needed for the studied models has to be calculated manually, which makes the procedure expensive, complex and laborious (Cosgrove et al., 2018), which may not reflect real values within dynamic processes (Xie et al., 2018).

3. Research Design

The research methodology began with a scoping review (de Mattos Nascimento et al., 2022), a diagnosis of the problems found in integrating the VSM tool with I4.0 technologies to make industrial processes more energy efficient that identifies the main energy, environmental and production process metrics, and the I4.0 technologies most frequently integrated with LM models. This information was then submitted to specialists for focus group discussion. The focus group rounds (Tong et al., 2007) aimed to analyse the importance of a lean model for energy management and to determine which were the most important metrics and technologies to include in the model.

In the Delphi study stage, a questionnaire was prepared by the authors to present the general objectives and most important metrics selected by the corresponding focus group to another group of specialists (Okoli & Pawlowski, 2004). Using the Fuzzy Delphi technique, the results related to the opinions of the participants were analysed quantitatively (A Ishikawa, 1993) to identify and classify the most relevant energy, environmental and production process metrics. A new questionnaire was then prepared with the metrics identified by the Fuzzy Delphi analysis to determine the interrelationships between the energy metrics on environmental and production process metrics using the Fuzzy DEMATEL technique (Garcia-Buendia et al., 2022). The Fuzzy Delphi method combines Fuzzy set theory and the traditional Delphi technique to improve the proficiency of expert judgement by reducing uncertainties (A Ishikawa, 1993), while the Fuzzy DEMATEL method is used to convert the cause and effect relationships (Garcia-Buendia et al., 2022) by identifying the most important energy metrics criteria that affect environmental and production process metrics criteria.

The main advantages of using Fuzzy Delphi are related to saving time on the questionnaire, saving costs, reducing the total number of surveys, and questionnaires increase the recovery rate, experts can fully express their opinions, ensuring completeness and consistency of opinions and taking into account the ambiguity that cannot be avoided during the study (Hsi-Mei Hsu & Chen-Tung Chen, 1996). The advantages of using Fuzzy DEMATEL can be described as overcoming the inevitable uncertainty, reducing the number of surveys, the semantic structure of forecast items can be explained, and the individual attributes of the expert can be described (Akira Ishikawa et al., 1993). The research, when using the integration of Fuzzy Delphi and Fuzzy DEMATEL, provides greater robustness in the results, allowing to extract from the interviewees a deep understanding of which criteria are most relevant, their ordering and also which are the strongest interrelationships, providing a broad understanding of the importance of the resulting metrics, encouraging a better use on the proposed model. All selected metrics were inserted in the RTEFM model and applied at the LabFaber 4.0 with the purpose of obtaining a depth empirical investigation of the application within a real environment (Quelhas et al., 2019).

Face validity requires the approval of nonresearchers regarding the validity of a study, being the arguably the most robust way to establish face validity is the involvement of domain experts, also known as subject matter experts, before (a priori), during, after (a posteriori), or throughout the research (Lucko & Rojas, 2010). This research was followed by a Focus Group (Yu et al., 2006), Delphi Study (del Caño & de la Cruz, 2002), and a case study (Rojas & Dossick, 2008) to establish face validity. An overview of the stages applied in the research is provided in Figure 2.

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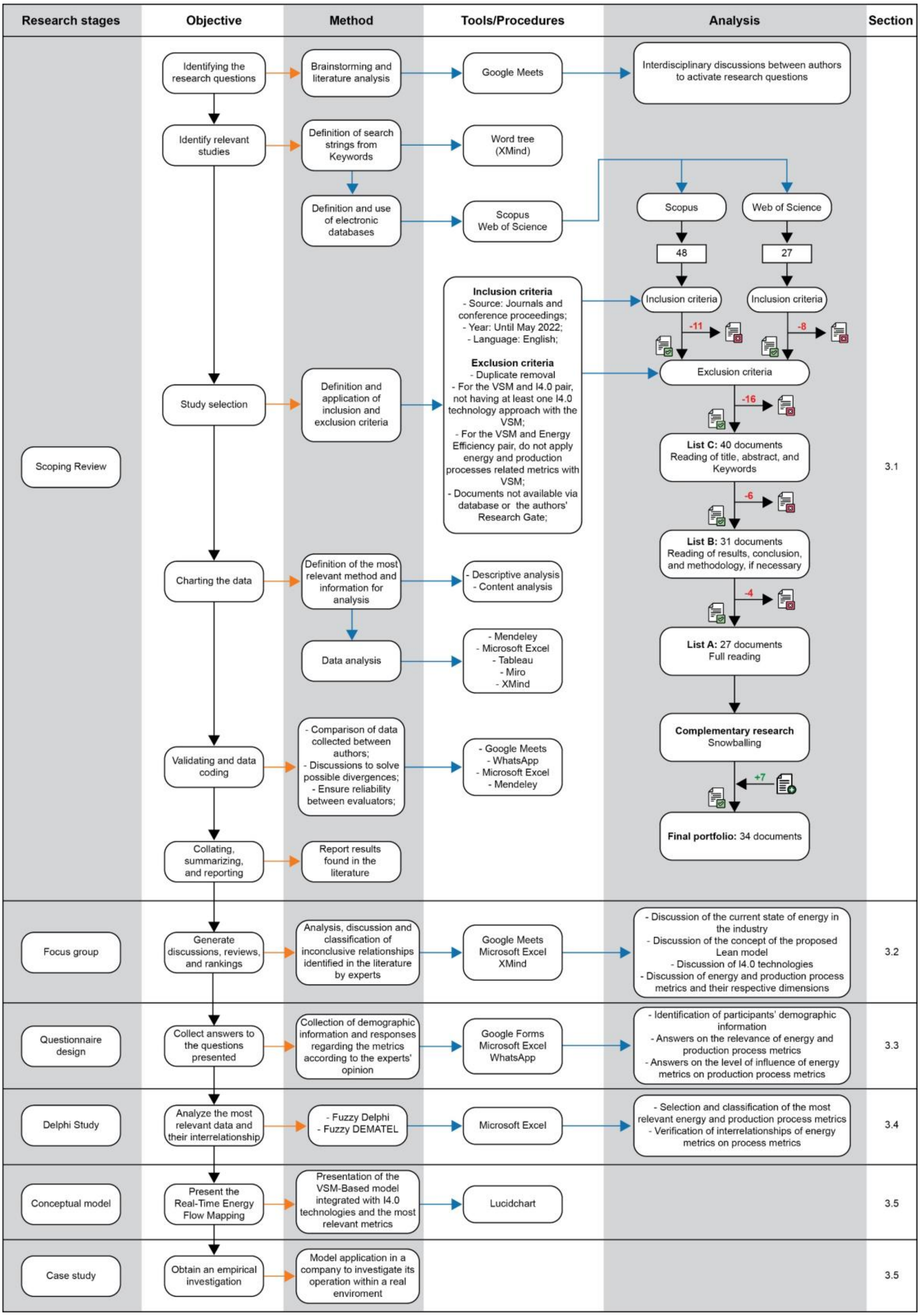

Figure 2. Research design of the study

3.1 Scoping Review

The scoping review executed in the first stage is a method that allows the literature to be mapped to comprehensively and efficiently evaluate the existing literature on framework propositions (Nascimento et al., 2022), summarizing complex and heterogenous topics (Di Pasquale et al., 2020). The scoping review was separated into five steps (Arksey & O'Malley, 2005): identifying the research questions, relevant studies, study selection, charting the data, and collating, summarizing, and reporting. An extra qualitative step has been added, aiming to improve the quality of analysis, called validating and data coding (Danese et al., 2018). The scoping review has recently been applied to several areas related to this study, e.g., VSM (Marin-Garcia et al., 2021), I4.0 technologies (Wilhelm et al., 2021), manufacturing (Di Pasquale et al., 2020), and others.

For reasons of transparency, it is important to detail how the entire review was carried out (Saunders et al., 2012). Also, identifying research questions (i), interdisciplinary discussions between authors, brainstorming, and literature analysis were realized, aiming to understand the state-of-the-art of energy management models and energy efficiency issues in the industrial sector and determine the most used I4.0 technologies and energy, environmental and production process metrics. A reasonable review provided the theoretical basis (Saieg et al., 2018) and identified research gaps (Webster & Watson, 2002). To identify relevant studies (ii), the research string was constructed (Saieg et al., 2018) with the aid of a word tree of relevant terms found in the literature (Gabriele et al., 2012), as shown in Figure 3. A portfolio was built using documents listed in Scopus and Web of Science (WoS) electronic databases, configured to execute the search by title, abstract and keywords.

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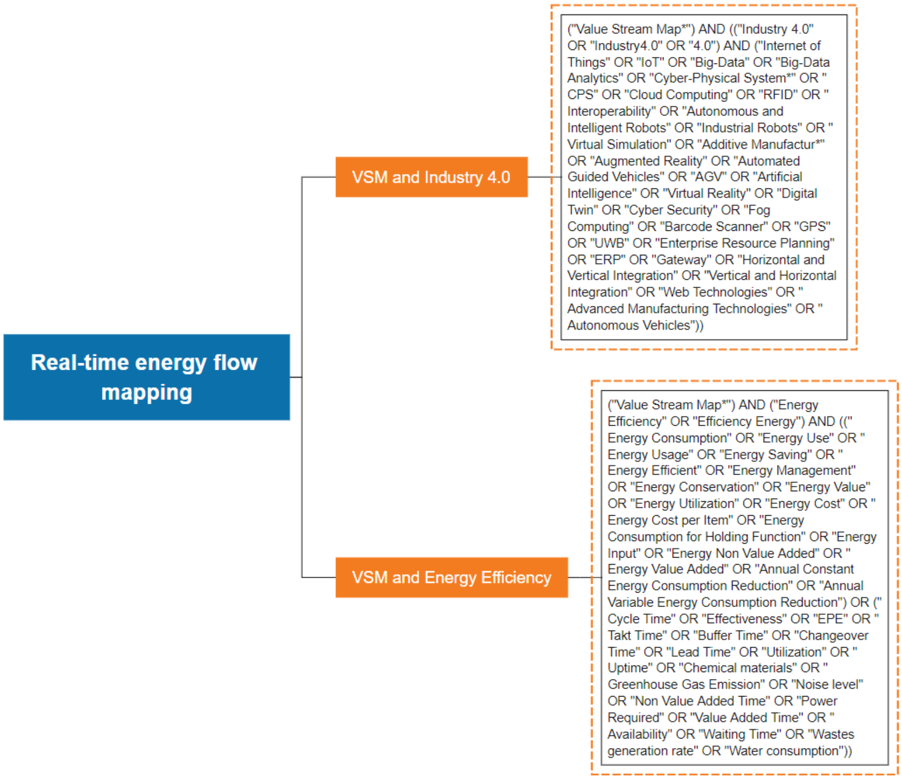

Figure 3. Search strings

The first pair (VSM and I4.0) found 34 documents, the second pair (VSM and Energy Efficiency) found 41 documents, and the search string using VSM, I4.0, and energy efficiency found 0 documents, generating 75 documents before the application of inclusion and exclusion criteria. Study selection (iii) was applied considering inclusion and exclusion criteria, where to inclusion criteria, only English and peer-reviews journals and conference proceedings documents were retrieved as they are considered the most reliable sources for literature reviews (Saunders et al., 2012). All publications up to May 2022 were used in the study, yielding a total of 40 documents. Any VSM and I4.0 pair papers without at least one I4.0 technology integrated with VSM, and any VSM and Energy Efficiency pair papers that did not demonstrate the application of energy, environmental and production process metrics with VSM to improve energy efficiency were discarded. Inclusion and exclusion criteria were applied to reduce any researcher interference or bias during selection (Siddaway, 2014).

The selected documents underwent a three-stage evaluation. Firstly, the titles, abstracts and keywords were read. Next, the methodology, results and/or findings, and conclusions were read. The final stage comprised a full reading of the selected documents.

A further seven documents were added to the final portfolio by snowballing complementary research, yielding a total of 34 publications to be used in this research. The scoping review identified the most used VSM-based models focused on energy efficiency, VSM-based models integrated with I4.0 technologies, energy, environmental and production process metrics, and I4.0 technologies most applied in conjunction with VSM.

Charting data (iv) was performed by defining which methods and information would be used for analysis, with descriptive (Núñez-Merino et al., 2020) and content analysis (Jose Arturo Garza-Reyes, 2015) being chosen for this study. Validating and data coding (v) enabled the comparison of the collected informations, in addition to the discussions to solve possible differences, guaranteeing the reliability, minimizing errors and bias of the evaluators (Caiado et al., 2022). Collating, summarizing, and reporting (vi) was performed using descriptive analysis of the main keys of the research, along with content analysis of the VSM-based models and their implementation barriers.

3.2 Focus Group

A focus group was used during the second stage. This is a research technique that uses participant interaction to generate data on topics previously defined by the researcher (D. L. Morgan, 1996) for discussion and to understand specialist perceptions (Krueger, 1994). This technique can, therefore, be considered a qualitative method that closely resembles the interview. Meetings must follow certain protocols with a moderator continually fomenting interaction among all the participants, who may or may not be influenced by the responses of the others involved (Oliveira & Freitas, 1998).

The main advantages of using focus groups in research are ease of execution, the ability to explore topics and generate hypotheses, the opportunity to collect data from group interaction (Krueger, 1994), high data speed, low cost compared to other methods, speed in providing the results and allowing the researcher to increase the sample size whenever necessary (Oliveira & Freitas, 1998). Focus group sessions should have between three and twelve participants (Kontio et al., 2008) and their segmentation has the advantage of building comparative dimensions into the entire research project and facilitating discussions by making the participants more similar to each other (D. Morgan, 1997). Table 2 lists the experts selected to participate in the focus group.

Table 2. Focus Group experts

Code	Experience	Specialities	Role	Country	Expert
A1	21 years	Industrial Technologies	Electrical Engineer	Brazil	Practitioner
A2	15 years	Sustainable Management Systems	Industrial Engineer	Spain	Academic
A3	23 years	Industrial Technologies	Electrical Engineer	Brazil	Practitioner
A4	20 years	Information Technologies	Computer Networker	USA	Practitioner
A5	5 years	Industrial Planning	Electrical Engineer	Brazil	Practitioner
A6	7 years	Energy Management Systems	Mechanical Engineer	Brazil	Practitioner
A7	5 years	Industrial Planning	Civil Engineer	Brazil	Practitioner

Table 2 presents the seven specialists selected for their perceived knowledge due to their educational level, research and/or professional experience (Nascimento et al., 2022) in engineering, technology or energy. Apart from these experts, all the sessions included a moderator to lead and drive the discussion. There were four sessions with a total duration of 281 minutes. The first interaction discussed the current state of energy in the industrial sector and how the proposed model could help to achieve better energy efficiency in industries. In the second and third iterations, the discussion revolved around the I4.0 technologies that would be essential to apply in the model and how energy efficiency could be achieved in an industrial environment. The fourth interaction determined the energy, environmental and production process metrics that would be the most relevant for better energy management and simultaneously identified which dimensions related to each metric were addressed.

Participants specialised in Industrial Technologies possessed a vast knowledge and experience of over 21 years working on industrial projects related to applied mechanics, industrial automation, hardware and software. The Sustainable Management Systems specialist was an academic with 15 years of experience who worked as a researcher and university lecturer in the areas of BIM, Lean Systems, Circular Economy, Industry 4.0, Lean 4.0 and Construction Life Cycle Project Management. The Energy Management Systems specialist had 7 years of experience working directly in the energy sector, in energy efficiency, electric mobility and hydroelectric and wind power plant projects. The IT specialist had 20 years of experience in software development for management systems. The Industrial Planning specialists had 5 years of experience working in project management and planning.

3.3 Questionnaire design and expert panel

The third stage considered the design and testing of the questionnaire used in the research and consisted of different phases to classify and clarify all the study information for the participants (Garcia-Buendia et al., 2022). The first phase dealt with demographic information such as each specialist's current role, total experience time and time performing their current role. The second phase elicited responses from the participants to evaluate the metrics according to the questions posed.

Before the discussions started, a brief initial explanation was given of the proposed conceptual model and the evaluated metrics' general definitions and how they would be used. The entire content of the questionnaires was previously tested among the authors to identify any inconsistencies, with preliminary access to the questionnaires being carried out for reading, answering and sending to guarantee that all the information was unambiguous. Although there is no rules regarding the minimum number of experts needed for a Delphi study (Moktadir et al., 2020), the recommendation is for ten to eighteen participants' opinions to be collected to reach a consensus (Okoli & Pawlowski, 2004). Twenty-four specialists who had not participated in the focus groups were selected using established criteria: a minimum of 12 years of experience in the industrial or academic sector, with specialities related to management, engineering, or energy. Table 3 gives the characteristics of the panel of experts who participated in the study.

Table 3. Composition of the expert panels

Characteristics	**n (%)**
Experience	
From 12 to 15 years	5 (20.83)
From 15 to 25 years	10 (41.67)
Over 25 years	9 (37.50)
Role	
Administration (Director, Manager and Coordinator)	13 (54.17)
Technical (Application Engineer, Industrial Engineer and Technical Consultant)	8 (33.33)
Commercial (Sales Engineer)	2 (8.33)
Research	1 (4.17)
Expert	
Practitioners	22 (91.67)
Academics	2 (8.33)
Qualification	
Engineering	20 (83.33)
Others	4 (16.67)

Table 3 lists all the selected specialists who participated in a two-round survey. Of these, 79.17% had over 15 years of professional experience and 83.33% had an academic background in engineering, which improved the quality of the responses. In the first round, a 5-point Likert scale from 1 = irrelevant to 5 = extremely relevant was used to select the most relevant metrics for inclusion in the model. In the second round, respondents had to indicate the influence of energy metrics metrics on environmental and production process metrics using the linguistic scale NI, LI, MI, HI and EI ('no influence', 'low influence', 'moderate influence', 'high influence' and 'extreme influence', respectively). All twenty-four experts participated in both rounds.

3.4 Fuzzy Delphi and Fuzzy DEMATEL study

In the fourth stage, the Fuzzy Delphi and Fuzzy DEMATEL techniques were used to analyse the answers to the questionnaires. Two distinct rounds were carried out, the first to understand which energy, environmental and production process metrics were the most relevant according to the experts' perceptions. After discarding the less relevant metrics, the second round identified the strongest interrelationships between the energy metrics on environmental and production process metrics. It is recommended that the same questionnaire is submitted to the experts more than once in each round for their predictions to converge (Akira Ishikawa et al., 1993). Two questionnaire submissions per round were established for the present study, giving a total of four submissions to be answered by the same participants.

3.4.1 Fuzzy Theory

Fuzzy set theory introduced the concept of membership function to handle different linguistic variables problems (B. Chang et al., 2011). Chang et al. (2000) state that this theory was adopted to convert highly uncertain linguistic preferences into quantitative values that continued to be based on human choices and maintained their qualitative characteristics. The defuzzification process reduces a series of conclusions of variable pertinence to a single output point (Cheung et al., 2005).

3.4.2 Fuzzy Delphi

The Fuzzy Delphi method integrates Fuzzy set theory with the traditional Delphi method to reduce any uncertainties related to the specialists' preferences, thereby improving the quality of the results obtained in the research (A Ishikawa, 1993). It was developed by Helmer and his associates as a long-term forecasting method that required repeated surveys of experts for the forecast values to converge (Akira Ishikawa et al., 1993).

Table 4. Corresponding triangular Fuzzy numbers for relevance scale

Scale	Linguistic term	Triangular Fuzzy Numbers (TFN)
1	No relevance (NR)	(0; 0; 0.25)
2	Low relevance (LR)	(0; 0.25; 0.50)
3	Moderate relevance (MR)	(0.25; 0.50; 0.75)
4	High relevance (HR)	(0.50; 0.75; 1.0)
5	Extreme relevance (ER)	(0.75; 1.0; 1.0)

Table 4 gives the triangular Fuzzy numbers that correspond to the linguistic terms. Tsai et al. (2020) demonstrated an assumption that the significance value of an attribute b is rated by a respondent a as $j = (x_{ab}, y_{ab}, z_{ab})$, $a = 1, 2, 3, \dots, n$ and $b = 1, 2, 3, \dots, m$. Thus, the j_b weight of the b attribute is computed as $j_b = (x_b, y_b, z_b)$, where $x_b = min(x_{ab})$, $y_b = (\prod_1^n y_{ab})^{1/n}$ and $z_b = max(z_{ab})$. According to Wu et al. (2016), the value of the convex combination D_b is generated using α cut, and in common situations, as shown by Lee et al. (2018), the adopted α value is normally 0.5 but can be adjusted depending on the experts' level of optimism or pessimism defined as 0 or 1. The calculation of the value of the convex combination can be expressed by Equation 1:

$$D_b = \int (u_b, l_b) = [\lambda u_b + (1 - \lambda) l_b] \qquad (1)$$

where:

$u_b = z_b - \alpha(z_b - y_b)$

$l_b = x_b - \alpha(y_b - x_b)$

$b = 1, 2, 3, \dots, m$

α = Expert's level of optimism

λ= Decision-maker's level of optimism

Lambda (λ), besides expresses a decision-maker's level of optimism, also stabilises the expert group's radical judgements. Therefore, $\delta = \sum_{a=1}^{n} \frac{D_b}{n}$ is the filter threshold of required attributes. If $D_b \geq \delta$, attribute b is accepted, otherwise it must be rejected (Garcia-Buendia et al., 2022).

3.4.3 Fuzzy DEMATEL

DEMATEL is an extended method for building and analysing structural models that can explain the influence relationships between complex criteria (B. Chang et al., 2011). This method is useful for visualising complex causal relationship structures with matrices or digraphs and is able to convert the relationship between the criteria causes and effects into a comprehensible structural model of the system (Falatoonitoosi et al., 2013).

Table 5. Corresponding triangular Fuzzy numbers for influence scale.

Scale	Linguistic terms	Triangular Fuzzy Numbers (TFN)
NI	No influence	(0; 0.1; 0.3)
LI	Low influence	(0.1; 0.3; 0.5)
MI	Moderate influence	(0.3; 0.5; 0.7)
HI	High influence	(0.5; 0.7; 0.9)
EI	Extreme influence	(0.7; 0.9; 1.0)

Table 5 gives the linguistic terms and their corresponding triangular Fuzzy numbers. Fuzzy DEMATEL uses the defuzzification technique to transform qualitative information into Fuzzy linguistic data, with the process generating crisp values from Fuzzy numbers. Then the left and right values are computed by minimum and maximum fuzzy numbers. The fuzzy membership functions $f_{ij}^k = \left(f_{l_{ij}}^k, f_{m_{ij}}^k, f_{r_{ij}}^k\right)$ are used to generate the total weighted values. Assuming that k experts participated in the evaluation process, the f_{ij}^k signifies the fuzzy weight of the i^{th} attribute's effect on the j^{th} attribute as assessed by expert k^{th}. The crisp values ate then presented in a total direct matrix, allowing a diagram to be drawn to simplify the analytical results. The cause and effect groups containing certain attributes represent the structured interrelashionships and important effects. A set of attributes is proposed (F), and certain pairwise interrelashionships are used to create the mathematical relations (Tsai et al., 2020). The proposed Fuzzy DEMATEL method is divided into 6 steps, as shown below:

Step 1. Normalise the Fuzzy numbers:

$$F_{ij}^k = \left(f_{l_{ij}}^k, f_{m_{ij}}^k, f_{r_{ij}}^k\right) = \left[\frac{l_{ij}^k - min\left(l_{ij}^k\right)}{\Delta}, \frac{m_{ij}^k - min\left(m_{ij}^k\right)}{\Delta}, \frac{r_{ij}^k - min\left(r_{ij}^k\right)}{\Delta}\right] \quad (2)$$

$$\Delta = max\left(r_{ij}^k\right) - min\left(l_{ij}^k, m_{ij}^k, r_{ij}^k\right) \quad (3)$$

where:

l_{ij}^k = Left TFN values

m_{ij}^k = Mean TFN values

r_{ij}^k = Right TFN values

Step 2. Compute right (*rv*) and left (*lv*) normalised values:

$$\left(lv_{ij}^{k}, rv_{ij}^{k}\right) = \left[\frac{f_{m_{ij}}^{k}}{1 + f_{m_{ij}}^{k} - f_{l_{ij}}^{k}}, \frac{f_{r_{ij}}^{k}}{1 + f_{r_{ij}}^{k} - f_{m_{ij}}^{k}}\right] \tag{4}$$

where:

$f_{l_{ij}}^{k}$ = Minimum normalised Fuzzy number

$f_{m_{ij}}^{k}$ = Mean normalised Fuzzy number

$f_{r_{ij}}^{k}$ = Maximum normalised Fuzzy number

Step 3. Compute the normalised crisp values (x):

$$x_{ij}^{k} = \frac{\left[lv_{ij}^{k}\left(1 - lv_{ij}^{k}\right) + \left(rv_{ij}^{k}\right)^{2}\right]}{\left(1 - lv_{ij}^{k} + rv_{ij}^{k}\right)} \tag{5}$$

where:

lv_{ij}^{k} = Left normalised value computed

rv_{ij}^{k} = Right normalised value computed

Step 4. Integrate the crisp values ($\tilde{x}$):

$$\tilde{x}_{ij} = \frac{x_{ij}^{1} + x_{ij}^{2} + \cdots + x_{ij}^{k}}{K} \tag{6}$$

where:

x_{ij}^{k} = Normalised crisp value computed

K= Total number of respondents

Step 5. Arrange the generalised direct relation matrix (G):

$$G = \left[\tilde{x}_{ij}\right]_{I \times J} \tag{7}$$

where:

$\tilde{x}_{ij}$ = Integrated crisp values

Step 6. Compute the normalised total direct relation matrix (T):

$$T = \tau \otimes G \tag{8}$$

$$\tau = \frac{1}{\max\left(\sum_{i=1}^{I} \tilde{x}_{ij}\right)} \tag{9}$$

where:

G = Generalised direct relation matrix

$\tilde{x}_{ij}$ = Integrated crisp values

3.5 Case study

The conceptual model was elaborated using the most relevant metrics resulting from the Fuzzy Delphi and Fuzzy DEMATEL study, together with the I4.0 technologies discussed by the focus group. This model was submitted to a case study for empirical validation. A case study is research approach that is used to generate in-depth, multi-faceted understanding of a complex issue in its real-life context (Crowe et al., 2011), especially when the limits between the phenomenon and the context are not clearly defined (Yin, 2009). Case study can be characterized in three main types: intrinsic, instrumemental, and collective (Stake, 1995). An intrinsic case study is normally used to learn about a unique phenomenon. The instrumental case study uses a particular case to gain a broader appreciation of a phenomenon, and the collective case study involves studying multiple cases simultaneously or sequentially aiming to generate a broad analysis of a particular issue (Crowe et al., 2011).

Case study can be used to explain, describe or explore events or phenomenon in the everyday contexts in which they occur, and can be classified in three typed regarding the research objective: descriptive, exploratory, and explanatory (Yin, 2009). Descriptive case study describe the phenomenon with its context, exploratory deals with little-know issues, trying to define hypotheses or propositions for future research, and explanatory aims explain relations of cause and effect from theory (Quelhas et al., 2019). A single, intrinsic, and explanatory case study was applied with the purpose of verifying and validating the functioning and behavior of the RTEFM model in a real manufacturing plant at the LabFaber 4.0 through practical tests. The implementation of the case study followed the following steps, as shown in Figure 4.

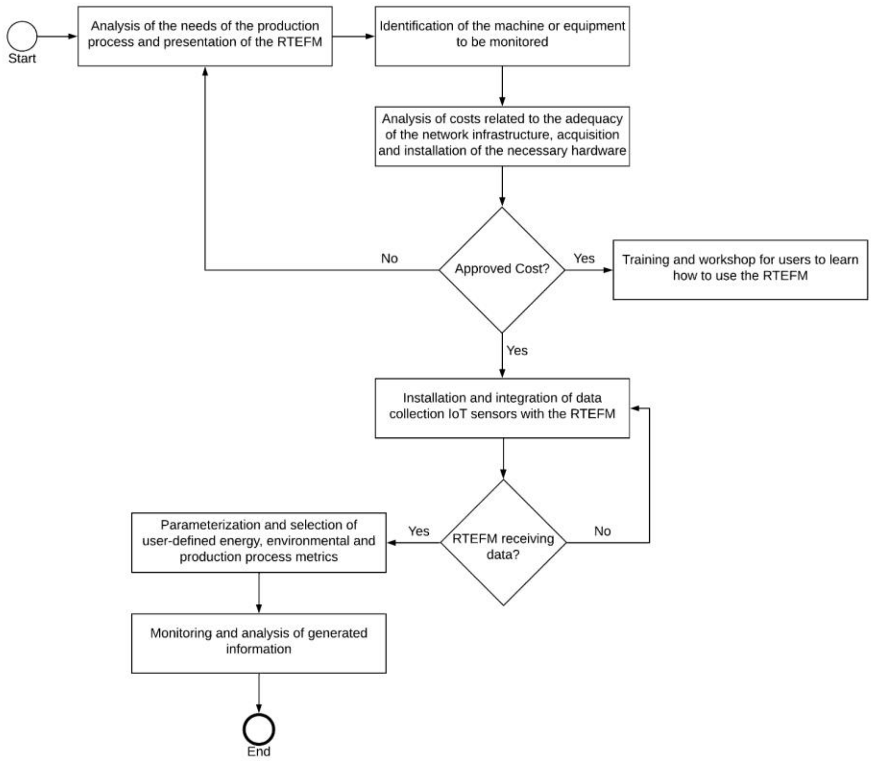

Figure 4. Overview of RTEFM implementation steps

After the severe and careful selection of the most relevant metrics and application in the conceptual model, the research sought, using the case study, to apply this model at the LabFaber 4.0, following the steps shown in Figure 4. The presentation of the model was premised on indicate to those responsible how the implementation and operation of the system would take place, seeking to understand the real and local needs in relation to energy issues, subsequently analyzing all the costs involved in the implementation and installation of the hardware responsible for the measurements, as well as the times related to the necessary stops of machines and equipment.

The identification of which machines were chosen for measurements and tests was based on the productivity criterion, choosing those that would possibly have the highest energy consumption. An analysis of the impacts to adapt the existing infrastructure for correct and satisfactory communication was carried out, followed by the installation of IoT measurement sensors, integrating them into the proposed management system. Training and workshops were carried out with the aim of preparing users to operate and monitor the system's dashboard, with all parameterization and selection of desired metrics being released and allowed, that is, as long as the parameters exist, the user would be free to use energy, production process, and enviromental metrics, and also create new metrics according to their needs. Finally, the monitoring and analysis of information would be available on the system panel through a web platform.

4. Analysis and Results

This section reports the qualitative and quantitative results obtained in the study, presents and discusses the main findings and proposes a new conceptual model called RTEFM, which has the ability to collect, store and visually display the energy flow map of machines and industrial production process equipment in real time.

4.1 Metrics, I4.0 technologies and opportunities in energy management

The scoping review included an analysis of the final portfolio of 34 documents, all of which were read in full and, as can be observed in Appendix A, the main energy, environmental and production process metrics, and main I4.0 technologies found in the document models were selected for discussion by the focus group.

Energy metrics are defined as follows: Energy Consumption is the energy consumption of machines or processes during a period of time determined by the user; Energy Usage is the amount of energy used by equipment; Energy Cost is the cost of energy used by a machine or during the industrial production process over a period of time determined by the user; Energy Input is the amount of energy consumed at the process input, excluding losses; Energy Value is the amount of energy used per unit of product or batch; Energy Utilisation is the percentage of the process’s total energy consumption used in the execution of a given activity; Non-Value-Added Energy is the amount of energy consumed by activities that do not generate value; Value-Added Energy is the amount of energy consumed by activities that generate value; Energy Cost per Item is the energy cost per unit of product or batch.

Environmental and production process metrics are defined as follows: Cycle Time is the amount of time required to produce a given item or batch; Lead Time is the total amount of time taken to deliver a product along the value chain; Greenhouse Gas Emissions is the amount of CO, CO2, H2S, NH3, NO2, SO2 and dust emitted during the production process; Power Required is the electrical power (apparent, active and reactive) required by the machine to perform activities; Waiting Time is the amount of time spent between productive stages, i.e., downtime, and Water Consumption is the amount of water used during the production process.

All the I4.0 technologies and energy, environmental and production process metrics were extensively discussed by the focus group, as was the need for a new conceptual model of energy management for industries. The purpose was to understand the current scenario of energy efficiency in the industrial sector and to identify the metrics that would represent the best combination for energy management according to expert perception. The experts expressed major concerns about energy losses during energy transformation processes and, in the industrial environment, the increasing complexity surrounding obtaining information on the energy consumption of installed equipment, which would limit stakeholders' ability to evaluate the flow of energy in processes and hamper their decision-making.

Therefore, the greatest advantage of our conceptual model would be its ability to inform the operator or any other interested party about the amount of energy being consumed by any particular machine or equipment in real time, which would allow to obtain both an overview and a snapshot of the entire energy flow in the process. For experts, one of the main barriers at the current time would be the difficulty of collecting data on the various extant industrial environments; however, they agree that these barriers would only be temporary thanks to developments in I4.0 technologies.

The focus group recognized that implementing Industry 4.0 technologies could potentially enhance an organization's market competitiveness, despite the significant investments required to adapt processes. According to the experts, the I4.0 technologies in the literature with the greatest synergies for inclusion in the proposed conceptual model are: (i) IoT for sending and receiving data from machines and industrial production processes; (ii) Edge Computing to reduce response times during data storage and processing; (iii) Cloud Computing for storing records and information on machines and equipment; (iv) Big-Data Analytics (BDA) to process and analyse the data obtained; (v) Web Technologies as a digital interface between the user and process data; (vi) Cyber-Security to ensure the security of all information transmitted over the network; (vii) Interoperability to promote complete communication between all devices on the network using protocol and format neutral information structures.

The focus group analysed the energy, environmental and production process metrics found in the literature and discussed those that would be the most efficient and relevant for application in an energy management model and their corresponding dimensions. The specialists had the inclusion of the Energy Consumption per Defective Item metric in the model, defined as the energy consumed per defective or damaged part and this was presented for analysis along with the other metrics. Only metrics that all focus group participants considered unnecessary were discarded. The metrics selected as the most relevant by the focus group can be seen in Figure 5 with their dimensions.

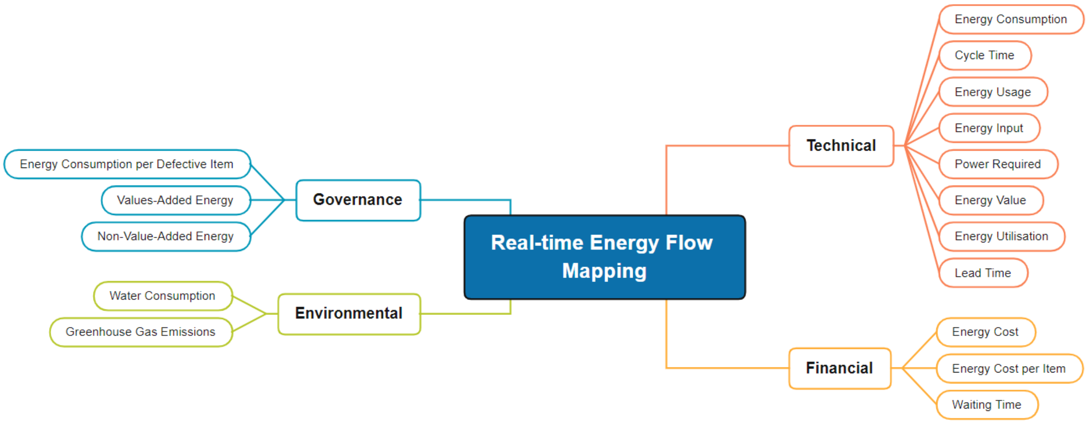

Figure 5. Metrics and dimensions

In this context, according to the information obtained from the scoping review and the extensive focus group discussion, the answer to RQ1 is that the use of RTEFM would enable companies to better manage their energy flow and also model energy consumption in their processes, as an effective energy management model is a major driver of cost reduction, increased performance and improved process sustainability indicators.

4.2 Most relevant energy, environmental and production process metrics

To answer RQ2, the Fuzzy Delphi technique was applied to identify the most relevant energy, environmental and production process metrics according to Equation 1. The experts' responses are given in Appendix B, in which the linguistic scales NR, LR, MR, HR and ER ('no relevance', 'low relevance', 'moderate relevance', 'high relevance' and 'extreme relevance') were used, as described in Table 4. The values 0.5 and 1 were adopted for α and λ respectively (P.-T. Chang et al., 2000). The calculated threshold (δ) value was 0.811 and the metrics whose convex combination (D_b) showed values lower than δ were rejected, as can be observed in Table 6.

Table 6. Fuzzy Delphi method results after screening

Dimension	Metrics	Code	u_b	l_b	D_b	Decision
Technical	Energy Consumption	E1	0.938	0.312	0.938	Approved
	Energy Usage	E2	0.916	-0.041	0.916	Approved
	Energy Input	E4	0.883	-0.383	0.883	Approved
	Energy Value	E5	0.866	-0.366	0.866	Approved
	Energy Utilisation	E6	0.858	0.017	0.858	Approved
	Cycle Time	P1	0.919	-0.044	0.919	Approved
	Lead Time	P2	0.500	0.000	0.500	Rejected
	Power Required	P4	0.877	-0.377	0.877	Approved
Financial	Energy Cost	E3	0.921	-0.046	0.921	Approved
	Energy Cost per Item	E9	0.899	-0.024	0.899	Approved
	Waiting Time	P5	0.832	-0.332	0.832	Approved
Governance	Non-Value-Added Energy	E7	0.500	0.000	0.500	Rejected
	Value-Added Energy	E8	0.500	0.000	0.500	Rejected
	Energy Consumption (Defective Item)	E10	0.842	-0.342	0.842	Approved
Environmental	Greenhouse Gas Emissions	P3	0.850	-0.350	0.850	Approved
	Water Consumption	P6	0.869	-0.369	0.869	Approved
Threshold δ	0.811					

As Table 6 shows, only three of the sixteen metrics analysed were rejected, namely Lead Time, Non-Value-Added Energy and Value-Added Energy. The most relevant metric for the technical dimension was Energy Consumption; for the financial dimension, Energy Cost; for the governance dimension, Energy Consumption per Defective Item and for the environmental dimension, Water Consumption.

4.3 Interrelationships between energy metrics on environmental and production process metrics

As Table 6 indicates, after identifying, classifying and selecting the most relevant energy, environmental and production process metrics, to answer RQ3, a new study was conducted to determine the strongest interrelationships between the studied metrics. The Fuzzy DEMATEL technique was applied in this phase to evaluate the influence between the energy metrics on environmental and production process metrics.

The first step in a Fuzzy DEMATEL analysis is to shape the initial direct relation matrices I using the information collected from the specialists. Appendix C gives an example using the data collected from Respondent 1. The responses from the respondents are used to generate individual initial direct relation matrices I. As can be seen in Table 5, as previously mentioned, the experts were asked to classify the influence of the energy metrics on environmental and production process metrics on the linguistic scale NI, LI, MI, HI, EI ('no influence', 'low influence', 'moderate influence', 'high influence' and 'extreme influence').

The design of the Fuzzy linguistic variables converts the initial direct relation matrices I into triangular Fuzzy numbers using the data in Table 5. Each linguistic variable is replaced by its corresponding number, as shown in Appendix D. The defuzzification process is conducted using Equations 2 and 4. Equation 5 uses the resulting crisp values to generate the direct relation matrices D in Appendix D.

Equation 6 is used to calculate the average values of the direct relation matrices D. Appendix E presents the generalised direct relation matrix G for energy, environmental and production process metrics, built with Equation 8. The total direct relation matrix T obtained by applying Equations 8 and 9 is presented in Table 7, which shows the interrelationships between the evaluated metrics.

Table 7. Total direct relation matrix T

	P1	P3	P4	P5	P6
E1	0.207	0.221	0.191	0.154	0.168
E2	0.186	0.188	0.168	0.145	0.141
E3	0.142	0.163	0.156	0.133	0.131
E4	0.101	0.188	0.167	0.111	0.093
E5	0.142	0.187	0.154	0.171	0.151
E6	0.209	0.224	0.161	0.238	0.169
E9	0.182	0.183	0.171	0.200	0.149
E10	0.124	0.138	0.124	0.187	0.147

Table 7 shows the strength of the relationships between the energy metrics on environmental and the production process metrics based on expert opinions. Higher values indicate a stronger interrelationship. As suggested by Garcia-Buendia et al. (2022), a percentage analysis was implemented to facilitate the interpretation and understanding of the results, with the percentiles 80 and 60 computed as limits representing strong and moderate influence on the relationship (0.188 and 0.170, respectively). See Table 8.

Table 8. Relevant relationships between energy metrics on environmental and production process metrics

	Energy metrics / Environmental and production process metrics	T		F	E	
		Cycle Time	Power Required	Waiting Time	Greenhouse Gas Emissions	Water Consumption
T	Energy Consumption					
	Energy Usage					
	Energy Input					
	Energy Value					
	Energy Utilisation					
F	Energy Cost					
	Energy Cost per Item					
G	Energy Consumption per Defective Item					
	Moderate influence (percentile 60)					
	Strong influence (percentile 80)					

Note: T (Technical dimension), F (Financial dimension), E (Environmental dimension), G (Governance dimension)

Thus, metric relationships with values above 0.170 (percentile 60) were considered to have a moderate influence (light grey) and metric relationships with values above 0.188 (percentile 80) were considered to have a strong influence (dark grey). Any interrelationships below 0.170 was considered to have an insufficient influence.

4.4 Proposal for Real-time Energy Flow Mapping

The proposed conceptual model is based on real-time data collection using IoT, information storage in Edge Computing and Cloud Computing, data analysis using BDA and presentation of information via a Web platform that can be customised to user needs. All traffic and information storage have layers of security via Cyber-Security. On the Web platform, the user can select metrics by dimension, relevance, influence or individually. New metrics can be registered providing that the parameters available during collection are respected. The entire architecture is shown in Figure 6.

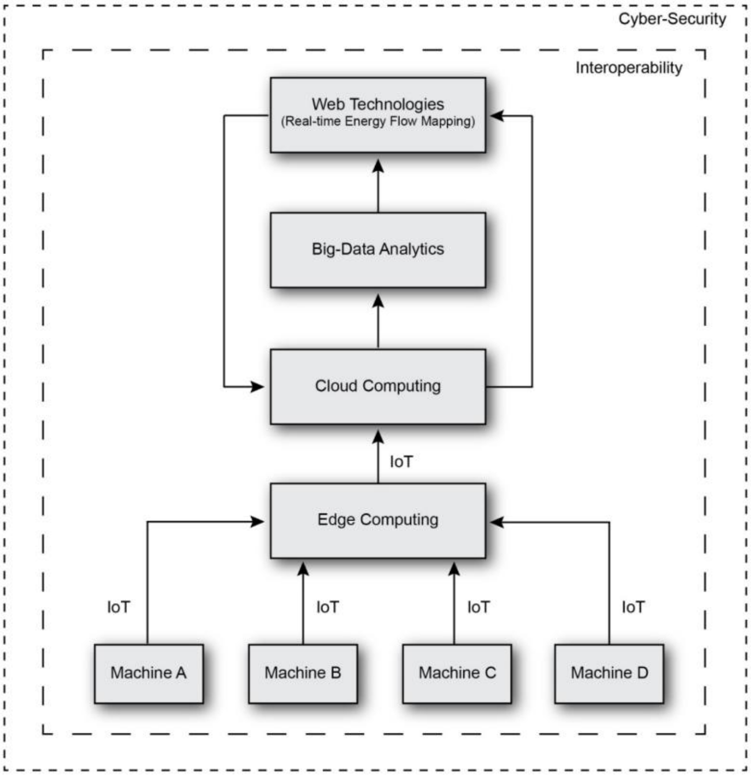

Figure 6. RTEFM, technological model

As shown in Figure 6, the great benefit of the model is its flexibility to adapt to different customer needs since its data collection structure via IoT sensors has a data structure protocol and neutral format. Interoperability between systems makes communication simpler. Another important point regarding the proposed model is its ability to allow the decision-maker to visualise the industrial process' entire energy flow map (see Figure 7). Users can use the stored energy consumption data to model equipment energy use with time series and, thus, detect anomalies and prevent any possible process failures before they occur.

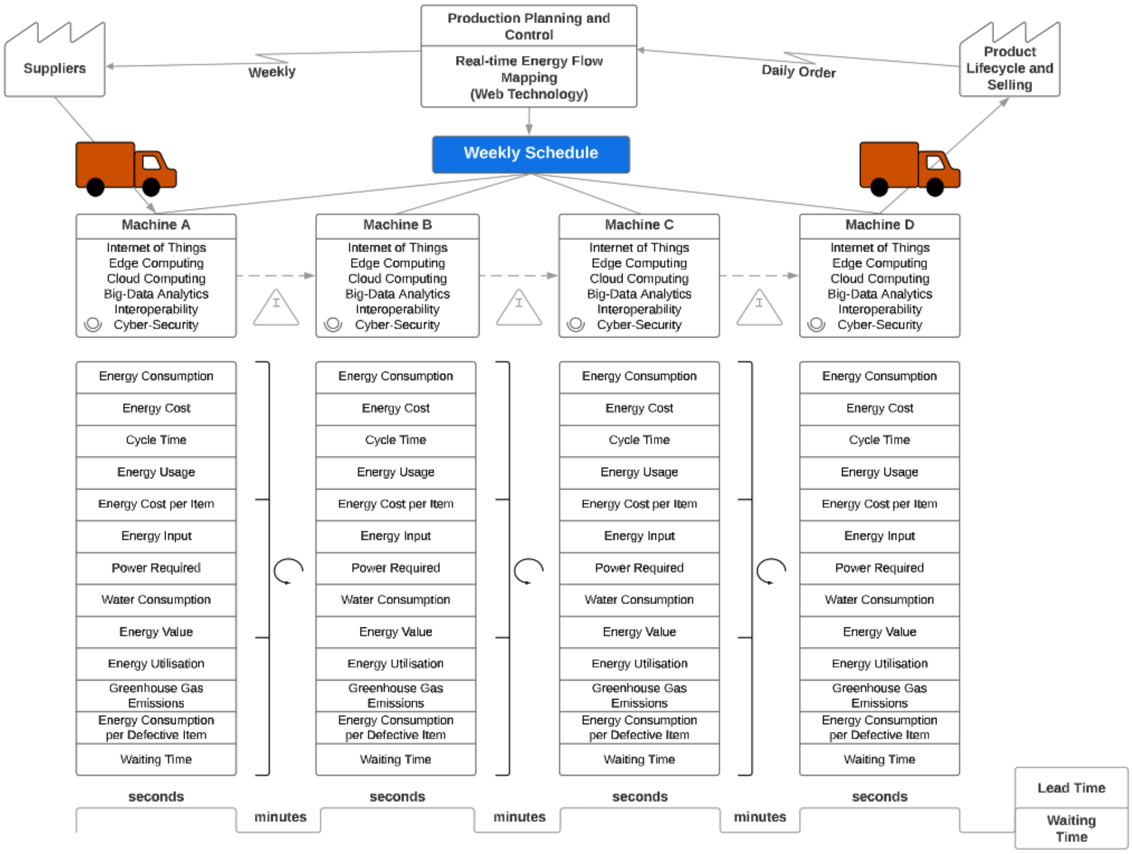

Figure 7. Overview of the proposed VSM-based model

As the example in Figure 7 shows, users have an overview of the energy flow in the selected process and can configure the information that they want to select, verify and analyse. If necessary, they can also determine the individual consumption of a particular machine or piece of equipment. A complete visualisation of the energy flow in processes allows for more rapid and precise interventions and also helps to improve energy efficiency in projects and act on the exact points where value is being lost. Another advantage is that future energy consumption can be forecast, so the economics of contracting the energy required can be improved.

4.5 Testing and operation in a real-world environment

A single case study was carried out at the LabFaber 4.0 to carry out an alpha test of the metrics selected in the research, together with tests related to customization according to the user's input parameters, functionality and ergometry. The system, based on a web platform, was integrated with IoT sensors, as shown in Figure 6, that collected real-time data regarding line voltages, phase voltages, phase current, frequency, active power, reactive power, apparent power, power factor, energy active, reactive energy,

Fontoura, L., de Mattos Nascimento, D., Neto, J.V., Garcia-Buendia, N., Garza-Rayes, J.A., Lima, G.B.A, Tortorella, G.L., Caiado, R.G.G., and Meiriño, M.J. (2023), "Real-time energy flow mapping: A VSM-based proposal for energy efficiency", *Journal of Cleaner Production*, Vol. 419, 137871, doi: https://doi.org/10.1016/j.jclepro.2023.137871.

apparent energy, and harmonic distortions. Although the RTEFM can monitor the entire process, from the acquisition stage to product delivery, a single case study was applied to the conveyor belt of the input stage to apply and verify the model. This conveyor belt is driven by a 4-pole squirrel cage motor powered by a 220Vac three-phase system with a frequency of 60Hz. The nameplate data of the applied motor informed by the manufacturer are electric power of 1.5kW (i); nominal rated current 6.65A (ii); power factor of 0.71 (iii); and electrical efficiency at 0.86% (iv). The test was carried out within an operational period of 4 hours, starting at around 8:00 am and ending at noon. A whole load was placed on the machine to test it as close to operational reality as possible. Energy consumption, energy cost, greenhouse gas emissions, cycle time, and waiting time metrics were selected for testing, as shown in Figure 8.

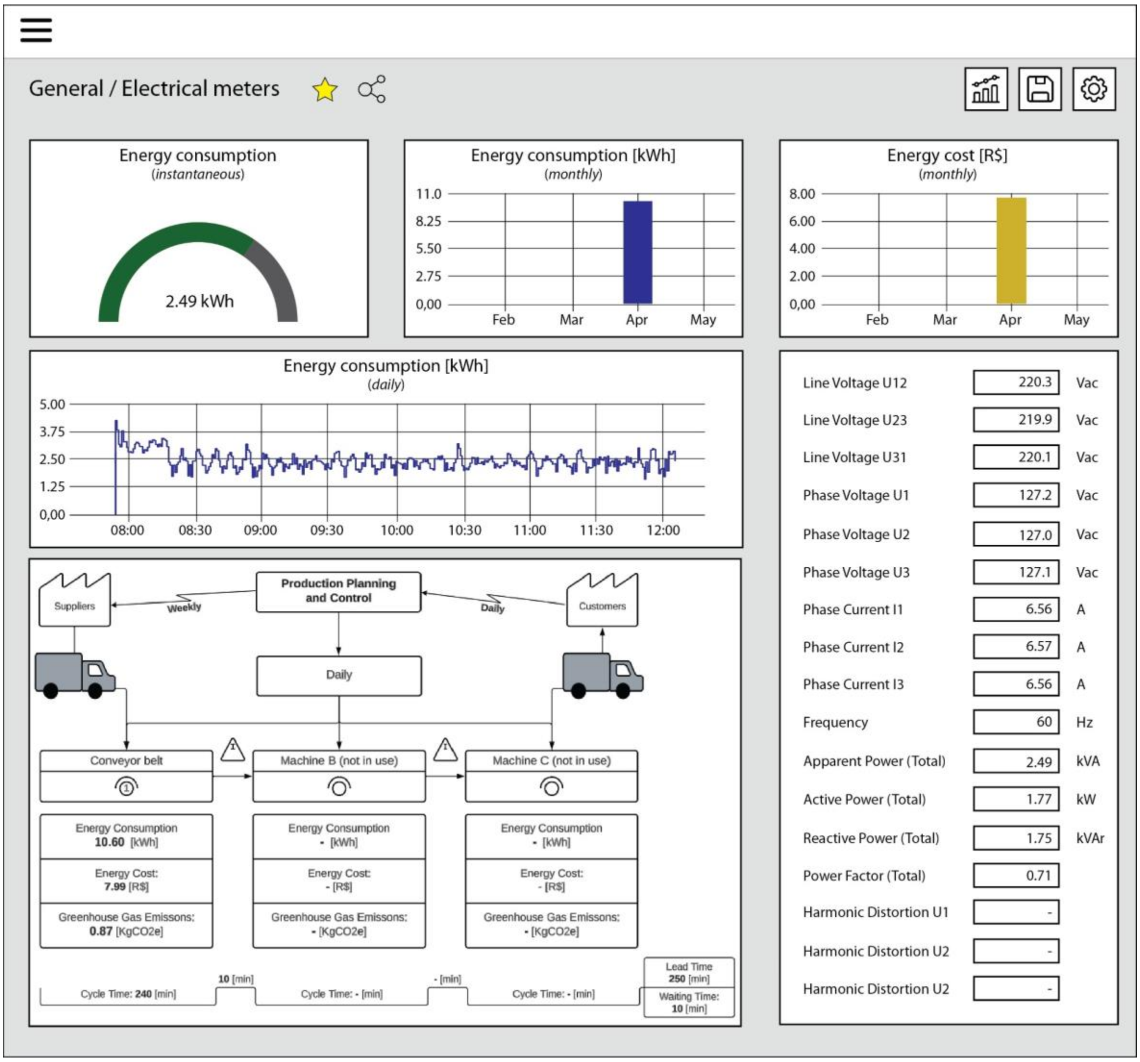

Figure 8. RTEFM Dashboard

To calculate the active power of electric motors in three-phase systems, Equation 10 is applied:

$$P_{3\emptyset} = \sqrt{3} \times VL \times In \times cos\varphi \qquad (10)$$

where:

$P_{3\emptyset}$ = Active power in three-phase systems

$VL =$ Line voltage

$In =$ Rated current

$cos\varphi =$ Power factor

The power informed by the manufacturer is the rotational mechanical power provided by the motor, that is, it is the power after the transformation of electrical energy into mechanical energy, therefore, taking efficiency into account. Thus, when applying Equation 10, an active power of 1.799kW and an apparent power of 2.53kVA are obtained. The calculation of the consumed energy is performed by multiplying the apparent or active power with time, usually expressed in kWh unit. Comparing with the values obtained by the model, the energy consumed is very close to the motor nominal, indicating that the system is operating at full load. The historical values of consumed energy can be observed in the test performed, and the user can select the period he wants to analyze the graphs.

This dashboard is applied to any metrics belonging to the model. Through this analysis, the user or stakeholders can check online on the RTEFM, thanks to the Cloud Computing and Web platform, whether the machines and equipment are operating as expected, comparing both with databook informations as well as its historical series. The calculation of the cost of energy is done by multiplying the energy consumed and the price of the contracted energy, which in this case was R$0.75 per 1kWh. The entire dashboard can be configured by the user, allowing in addition to the selection and creation of new metrics, also the arrangement of the entire layout for better visualization. At the bottom of the dashboard, a VSM of the process is shown, with the purpose of facilitating the user in selecting which steps he wants to carry out a more specific monitoring, or else, if he wants, the entire system.

In this way, the RTEFM model was applied in a real test of a conveyor belt, which is part of a manufacturing process. The results obtained were consistent with expectations, as well as its ability to promote a complete visualization of the system. Stakeholders, using the tool, will be able to understand possible energy and production process improvements, fault corrections, budget forecasting, and others. In a simple operational demonstration, the test was able to allow the visualization of the energy consumed (technical dimension), energy cost (financial dimension), and greenhouse gas emissions (environmental dimension).

5. Discussion

The present study was conducted using qualitative and quantitative techniques to understand the state-of-the-art of LM models focused on energy and how these models could improve energy efficiency in industries (RQ1); to identify the I4.0 technologies whose inclusion in the model is essential and determine the most relevant energy, environmental and production process metrics (RQ2) and their interrelationships (RQ3).

RTEFM fills the gap in the literature regarding VSM-based LM models to improve energy efficiency by monitoring energy consumption (Xie et al., 2018) through the dynamic energy flow mapping of production processes (Sihag & Sangwan, 2019). The use of I4.0 technologies such as IoT (Buer et al., 2018), BDA (Valamede & Akkari, 2020) and Cloud Computing (Ilangakoon et al., 2021) enables the proposed model to meet the needs of lean tools to leverage energy practices with real-time data traffic.

The proposed model can identify the area with the greatest potential for energy savings through changes in operational behaviour (Cosgrove et al., 2018) that reduce total energy consumption and environmental impacts (Estrada-Gonzalez et al., 2020). The model is also capable of detecting non-value-added energy consumption (Keskin et al., 2012), identifying energy waste (Jia et al., 2017), and analyse the effects of overloads and energy variability (Baysan et al., 2019), helping decision-makers to improve energy savings and budget forecasts (Verma & Sharma, 2019). As one of the functions of the model is energy modelling, a history of the machine's energy consumption behaviour will be present in the database, making it possible to identify any behavioural changes in the energy consumption of the process, that is, if the machine has not undergone changes related to load or process speed, an increase in energy consumption can indicate maintenance needs, which, if not detected, can cause breakdowns and failures, in addition to unnecessary energy consumption, directly impacting the environment. However, the model is not only limited to these measurements; it is possible and feasible to add metrics related to greenhouse gas emissions or water consumption in the processes, generating its time series, allowing a complete analysis and monitoring of the entire production process, impacting directly and positively on environmental issues.

All the information generated by the model is available dynamically due to the use of I4.0 technologies to improve real-time data collection (Buer et al., 2018). IoT sensors collect all the available data from machines and equipment (Camgoz-Akdag et al., 2018) with the information then sent to Edge Computing to reduce network latency and congestion generated by their offload from end-device tasks (Fernández-Cerero et al., 2020). Cloud Computing is used to store received data packages (Wagner et al., 2018) for further data and information analysis using BDA (Mayr et al., 2018).

RTEFM and the energy, environmental and production process metrics are available via Web Technologies for data integration (Jirkovsky et al., 2017). Cyber-Security technology is implemented to protect networks and data and guarantee the reliability of communications, resources and information management (Valamede & Akkari, 2020). Interoperability between systems is essential as it enables the model to be modular and flexible, and implementable in any type of industrial equipment (Hermann et al., 2015).

The results obtained from the scoping review and the focus group provided a solid basis for understanding the barriers to implementing a lean energy management model, including the identification of the most used energy, environmental and production process metrics. The most important barriers to implementing the model were found to be the lack of organisational procedures, the lack of adequate knowledge and the company's limited financial resources (Palm & Thollander, 2010), and these were subsequently categorised as organisational, behavioural and economic dimensions (Johansson & Thollander, 2018).

The scoping review showed that using VSM-based models to boost energy efficiency brings both technical and financial benefits (Verma & Sharma, 2019). The Fuzzy Delphi study identified thirteen energy, environmental and production process metrics whose technical and financial dimensions afforded the metrics the highest convex combination values: 53.85% and 23.08% participation, respectively. Therefore, companies using the proposed model are expected to be able to improve their production processes' technical and financial characteristics as spiralling energy demand is directly influenced by economic growth (Keskin et al., 2012).

The three most relevant energy metrics identified in the Fuzzy Delphi study were Energy Consumption, Energy Cost and Energy Usage. Together, these metrics represent approximately 41.76% of the most cited energy metrics found in the scoping review, followed by Energy Consumption at only 17.58%. Cycle Time, Power Required and Water Consumption were identified as the three most relevant environmental and production process metrics. Cycle Time was the most cited metric in the scoping review with approximately 27.27%. It is interesting to note that, although relevant according to the analyses, Power Required (Bettoni et al., 2015) and Water Consumption (Rukmayadi et al., 2016) were only mentioned once each in the literature.

Fuzzy DEMATEL identified sixteen interrelationships between energy metrics on environmental and production process metrics, on the influence scale adopted, in which percentiles 80 and 60 were computed as limits representing strong and moderate influence, respectively (Garcia-Buendia et al., 2022). It should be highlighted that the Energy Utilisation metric appears in both first and second place in Table 7 due to its powerful influence on Waiting Time and Greenhouse Gas Emissions. The relationship between Energy Consumption and Greenhouse Gas Emissions ranked third. Figure 9 presents a summary of how and which metrics were selected.

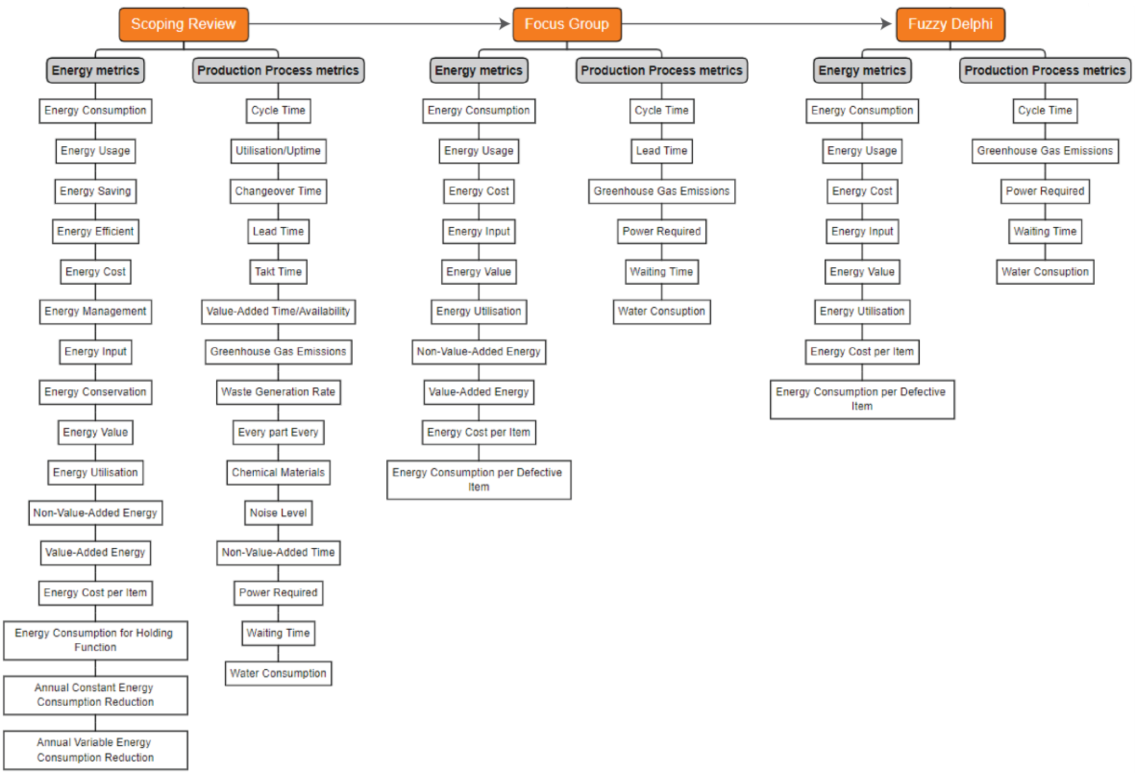

Figure 9. Metrics selection, overview

Figure 9 gives a concise overview of how all the metrics were analysed and selected in the scoping review. Energy Consumption per Defective Item was added at the suggestion of the focus group. Although Energy Cost was the most relevant financial dimension and Water Consumption the most relevant environmental dimension, according to Table 8, none of these metrics had a strong or moderate influence on any other metrics in the study. Regarding the financial dimension, the respondents considered that Energy Cost per Item would have a stronger interrelationship with most environmental and production process metrics.

The environmental dimension Greenhouse Gas Emissions metric presented the highest number of interrelationships with energy metrics, demonstrating the concern of the specialists who participated in the study to assess the need to monitor the relationship between energy and environmental metrics as emissions due to energy demand have risen in recent years (Schönemann et al., 2016), with industry responsible for 23% of CO2 emissions in the world (IEA, 2021a). Another important interrelationship demonstrates that attention should be paid to energy when it is not actually producing to identify losses that may be prevented or reduced (Bettoni et al., 2015). Table 9 shows a comparison between of the RTEFM and the others VSM-Based models with a focus on energy efficiency found in literature.

Table 9. Comparison between VSM-Based models

Models	**I4.0 technologies approach**	**Energy approach**				**Production Process approach**	**Environmental approach**
		Consumption	**Financial**	**Modelling and performance**	**Customization**		
RTEFM	X	X	X	X	X	X	X
EVSM		X				X	
IEVA		X				X	
TVSM		X				X	X
GVSM		X				X	X
VVLD		X	X			X	X
LCAVSM		X	X			X	

To summarise, as shown in Table 9, the RTEFM was developed using various data sources and expert's perceptions. Both qualitative and quantitative methods were applied for greater rigour in the analyses to identify all the I4.0 technologies, energy, environmental and production process metrics, used in the previous research through a scoping review (de Mattos Nascimento et al., 2022) and a focus group (Machado et al., 2021). Fuzzy Delphi was then used to identify the most relevant metrics (Garcia-Buendia et al., 2022) and Fuzzy DEMATEL to establish the strongest interrelationships (Ashtiani

Araghi & Vosoughifar, 2023), being applied in a case study at the LabFaber 4.0 for a face validity (Rojas & Dossick, 2008).

Managers, technicians and users, or all interested stakeholders, will be able to monitor the entire flow of processes, from metrics of productive processes as well as metrics related to energy, and can even create their metrics from existing parameters to allow complete and quick decision-making. This monitoring will be carried out in real-time and will also allow, through energy modelling, to compare with the historical behaviour of the machines from time series. The model will help organizations in an unprecedented way in all aspects of the ESG (Environmental, Social and Governance), as it will allow better use of the employees' work, improvement and technical training, better control of processes, reduction losses, reduction of machine downtime, greater capacity for budget forecasting for energy acquisition, reduction through energy control environmental and social impacts, and others. Therefore, the model would benefit not only the organization but society as a whole.

6. Conclusions

The reserach managed to go from the literature review to the application of a new LM model in a satisfactory way, being able to integrate energy, environmental and productive processes metrics in favor of energy efficiency in the processes. This entire model was able to obtain information in real time with web access to data thanks to the integration with I4.0 technologies. The model was tested by users of the company LabFaber 4.0, where the results were compared with the equipment databook, satisfactorily promoting a detailed dashboard referring to energy consumption, energy cost, greenhouse gas emissions, cycle time and waiting time. For this, a RTEFM model has been presented that integrates IoT, Edge Computing, Cloud Computing, BDA, Web Technologies, Interoperability and Cyber-Security technologies, and the most relevant energy, environmental and production process metrics. The integration of a VSM-based approach with I4.0 technologies and energy efficiency metrics was explored to answer the study's three RQs.

After selecting the metrics through the scoping review, the study included four sessions with specialists in focus groups that discussed the current state of energy in the industrial sector, the proposed management model, how to achieve energy efficiency in industries, I4.0 technologies and energy, environmental and production process metrics. The metrics selected after extensive discussions by the focus group participants were used

Fontoura, L., de Mattos Nascimento, D., Neto, J.V., Garcia-Buendia, N., Garza-Rayes, J.A., Lima, G.B.A, Tortorella, G.L., Caiado, R.G.G., and Meiriño, M.J. (2023), "Real-time energy flow mapping: A VSM-based proposal for energy efficiency", *Journal of Cleaner Production*, Vol. 419, 137871, doi: https://doi.org/10.1016/j.jclepro.2023.137871.

in two rounds of questionnaires for a subsequent Delphi study to understand the respondents' opinions and determine the most relevant metrics and their interrelationships. The resulting metrics were applied in the proposed model in conjunction with the I4.0 technologies. A case study was applied to test and validate the functionality of the model.

From a theoretical point of view, our investigation using a scoping review revealed a lack of VSM-based lean energy management models integrated with I4.0 technologies. Deep studies were carried out to ascertain the state-of-the-art of energy efficiency in the industrial sector and to identify the main lean models focused on energy management, the most discussed I4.0 technologies and the most used metrics. The concept of sustainable development is clearly on the agenda around the world and that issues related to efficient electricity consumption in production processes and the reduction of energy costs are some of the industrial sector's main concerns. From a practical point of view, managers using the RTEFM tool would be able to map the entire energy flow in their production processes in real-time and online, using a Web plataform, thus enabling more accurate and faster decision-making and cost reductions and increasing their market competitiveness. Allied to this, the tool would also allow the modeling of energy consumption through time series, making it possible to identify equipment failures due to behavioral changes in its electrical consumption, thus reducing machine downtime. Another important advantage in using the model would be the identification of equipment and machines with less clean technology, using continuous and preventive monitoring of production processes. Therefore, RTEFM, by constantly monitoring energy, environmental and production process metrics, would provide, in addition to increasing productivity, the development and adoption of cleaner production technologies by stakeholders, promoting the efficient use of natural resources in processes productive processes, including reducing the emission of greenhouse gases, causing a systematic reduction of environmental impacts.

One limitation of this study is the concentration of respondents in a single country, Brazil. Therefore, the responses to the questionnaires may have shown some regional bias in the experts' perceptions of the metrics' relevance and influence, and it is interesting to carry out further research with experts from other countries. However, this is a minor limitation as the criterion for their selection was that they should be qualified professional specialists with long experience in the industry. Another limitation is that the model was applied to a conveyor belt that is part of a much larger process, thus isolating the results in a point analysis. Therefore, regarding future research, the RTEFM can be applied in a complete process, allowing a complete analysis of the flow of information, materials and energy. One of the great advantages of the model is, precisely, its flexibility of implementation and integration, since the entire system can be customised to the organisation's needs while overcoming the concern about systems interoperability through protocol and format neutral information structures.

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Appendix

Appendix A. Energy metrics, environmental and production process metrics, and I4.0 technologies.

	References
Energy metrics	
Energy Consumption	Baysan et al., 2019; Bettoni et al., 2015; Cosgrove et al., 2018; Estrada-Gonzalez et al., 2020; Garza-Reyes et al., 2018; Jia et al., 2017; Keskin et al., 2012; Muller et al., 2014; Müller et al., 2014; Rukmayadi et al., 2016; Schönemann et al., 2016; Sihag & Sangwan, 2019; Svensson & Paramonova, 2017; Thanki & Thakkar, 2016; Verma & Sharma, 2019; Xie et al., 2018
Energy Usage	Baysan et al., 2019; Bettoni et al., 2015; Cosgrove et al., 2018; Estrada-Gonzalez et al., 2020; Garza-Reyes et al., 2018; Jia et al., 2017; Keskin et al., 2012; Müller et al., 2014; Rukmayadi et al., 2016; Sihag & Sangwan, 2019; Svensson & Paramonova, 2017; Thanki & Thakkar, 2016; Verma & Sharma, 2019; Xie et al., 2018
Energy Saving	Baysan et al., 2019; Bettoni et al., 2015; Cosgrove et al., 2018; Estrada-Gonzalez et al., 2020; Jia et al., 2017; Keskin et al., 2012; Melsas & Rosin, 2017; Muller et al., 2014; Rukmayadi et al., 2016; Sihag & Sangwan, 2019; Svensson & Paramonova, 2017; Verma & Sharma, 2019; Xie et al., 2018
Energy Efficiency	Baysan et al., 2019; Bettoni et al., 2015; Cosgrove et al., 2018; Keskin et al., 2012; Müller et al., 2014; Rukmayadi et al., 2016; Sihag & Sangwan, 2019; Svensson & Paramonova, 2017; Thanki & Thakkar, 2016; Verma & Sharma, 2019; Xie et al., 2018
Energy Cost	Baysan et al., 2019; Bettoni et al., 2015; Cosgrove et al., 2018; Jia et al., 2017; Müller et al., 2014; Schönemann et al., 2016; Sihag & Sangwan, 2019; Thanki & Thakkar, 2016; Xie et al., 2018
Energy Management	Baysan et al., 2019; Bettoni et al., 2015; Cosgrove et al., 2018; Garza-Reyes et al., 2018; Jia et al., 2017; Svensson & Paramonova, 2017
Energy Input	Cosgrove et al., 2018; Estrada-Gonzalez et al., 2020; Muller et al., 2014; Müller et al., 2014; Svensson & Paramonova, 2017; Verma & Sharma, 2019
Energy Conservation	Baysan et al., 2019; Melsas & Rosin, 2017; Svensson & Paramonova, 2017; Verma & Sharma, 2019
Energy Value	Bettoni et al., 2015; Sihag & Sangwan, 2019; Verma & Sharma, 2019
Energy Utilisation	Baysan et al., 2019; Keskin et al., 2012
Non-Value-Added Energy	Bettoni et al., 2015; Verma & Sharma, 2019
Value-Added Energy	Bettoni et al., 2015; Verma & Sharma, 2019
Energy Cost per Item	Schönemann et al., 2016
Energy Consumption for Holding Function	Bettoni et al., 2015
Annual Constant Energy Consumption Reduction	Melsas & Rosin, 2017
Annual Variable Energy Consumption Reduction	Melsas & Rosin, 2017
Environmental and Production process metrics	
Cycle Time	Baysan et al., 2019; Cosgrove et al., 2018; Estrada-Gonzalez et al., 2020; Jia et al., 2017; Keskin et al., 2012; Melsas & Rosin, 2017; Muller et al., 2014; Müller et al., 2014; Rukmayadi et al., 2016; Schönemann et al., 2016; Sihag & Sangwan, 2019; Svensson & Paramonova, 2017; Thanki & Thakkar, 2016; Verma & Sharma, 2019; Xie et al., 2018
Utilisation/Uptime	Baysan et al., 2019; Bettoni et al., 2015; Estrada-Gonzalez et al., 2020; Jia et al., 2017; Keskin et al., 2012; Muller et al., 2014; Müller et al., 2014; Verma & Sharma, 2019; Xie et al., 2018
Changeover Time	Baysan et al., 2019; Jia et al., 2017; Keskin et al., 2012; Müller et al., 2014; Rukmayadi et al., 2016; Sihag & Sangwan, 2019; Svensson & Paramonova, 2017; Verma & Sharma, 2019
Lead Time	Muller et al., 2014; Müller et al., 2014; Schönemann et al., 2016; 28; Thanki & Thakkar, 2016; Verma & Sharma, 2019
Takt Time	Baysan et al., 2019; Bettoni et al., 2015; Thanki & Thakkar, 2016
Value-Added Time/Availability	Jia et al., 2017; Müller et al., 2014; Thanki & Thakkar, 2016
Greenhouse Gas Emissions	Rukmayadi et al., 2016; Sihag & Sangwan, 2019
Waste generation rate	Baysan et al., 2019; Rukmayadi et al., 2016
Every Part Every (EPE)	Jia et al., 2017

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Chemical materials	Rukmayadi et al., 2016
Noise level	Rukmayadi et al., 2016
Non-Value-Added Time	Müller et al., 2014
Power Required	Bettoni et al., 2015
Waiting Time	Xie et al., 2018
Water consumption	Rukmayadi et al., 2016
I4.0 technologies	
Internet of Things (IoT)	Balaji et al., 2020; Boonsothonsatit et al., 2020; Buer et al., 2018; Camgoz-Akdag et al., 2018; Fortuny-Santos et al., 2020; Huang et al., 2019; Ilangakoon et al., 2021; Mayr et al., 2018; Pagliosa et al., 2021; Pasi et al., 2020; Phuong & Guidat, 2018; Ramadan et al., 2020; Tran et al., 2021; Wagner et al., 2018
Big-Data Analytics (BDA)	Buer et al., 2018; Fortuny-Santos et al., 2020; Ilangakoon et al., 2021; Mayr et al., 2018; Pagliosa et al., 2021; Pasi et al., 2020; Phuong & Guidat, 2018; Ramadan et al., 2020; Tran et al., 2021; Valamede & Akkari, 2020; Wagner et al., 2018
Industrial Robots	Benzi et al., 2018; Boonsothonsatit et al., 2020; Buer et al., 2018; Fortuny-Santos et al., 2020; Ilangakoon et al., 2021; Mayr et al., 2018; Pagliosa et al., 2021; Pasi et al., 2020; Phuong & Guidat, 2018; Ramadan et al., 2020; Valamede & Akkari, 2020
Cyber-Physical Systems (CPS)	Boonsothonsatit et al., 2020; Buer et al., 2018; Fortuny-Santos et al., 2020; Huang et al., 2019; Mayr et al., 2018; Pagliosa et al., 2021; Ramadan et al., 2020; Tran et al., 2021; Wagner et al., 2018
Cloud Computing	Fortuny-Santos et al., 2020; Huang et al., 2019; Ilangakoon et al., 2021; Pagliosa et al., 2021; Pasi et al., 2020; Ramadan et al., 2020; Valamede & Akkari, 2020; Wagner et al., 2018
Integration and Interoperability	Fortuny-Santos et al., 2020; Huang et al., 2019; Pagliosa et al., 2021; Pasi et al., 2020; Phuong & Guidat, 2018; Ramadan et al., 2020; Wagner et al., 2018
Additive Manufacturing (AM)	Fortuny-Santos et al., 2020; Ilangakoon et al., 2021; Mayr et al., 2018; Pagliosa et al., 2021; Pasi et al., 2020; Valamede & Akkari, 2020
Augmented Reality (AR)	Ilangakoon et al., 2021; Mayr et al., 2018; Pagliosa et al., 2021; Valamede & Akkari, 2020; Wagner et al., 2018
Virtual Simulation (VS)	Abideen & Mohamad, 2021; Pagliosa et al., 2021; Valamede & Akkari, 2020
Virtual Reality (VR)	Mayr et al., 2018; Tran et al., 2021; Wagner et al., 2018
Digital Twin	Mayr et al., 2018; Tran et al., 2021
Cyber-Security	Pasi et al., 2020; Valamede & Akkari, 2020
Fog Computing	Ilangakoon et al., 2021

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Appendix B. Fuzzy Delphi responses.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	P1	P2	P3	P4	P5	P6
M1	ER	ER	ER	HR	MR	MR	LR	HR	HR	MR	ER	ER	ER	ER	MR	HR
M2	HR	HR	HR	HR	HR	HR	ER	HR	HR	ER	ER	ER	MR	MR	HR	MR
M3	HR	HR	HR	HR	HR	MR	MR	HR	HR	MR	ER	ER	HR	HR	HR	HR
M4	HR	HR	HR	HR	HR	HR	MR	HR	HR	MR	ER	ER	MR	HR	HR	MR
M5	ER	HR	HR	HR	HR	HR	HR	ER	HR	MR	HR	ER	HR	ER	MR	HR
M6	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER
M7	ER	ER	ER	ER	HR	HR	ER	ER	HR	ER	ER	HR	ER	ER	ER	ER
M8	HR	MR	MR	LR	LR	ER	NR	NR	MR	HR	ER	NR	MR	LR	ER	LR
M9	ER	HR	HR	HR	HR	HR	LR	ER	HR	HR	HR	HR	HR	ER	LR	HR
M10	HR	ER	ER	HR	ER	HR	HR	MR	ER	MR	ER	HR	HR	ER	HR	HR
M11	ER	ER	ER	HR	ER	HR	ER	ER	ER	ER	HR	HR	ER	ER	HR	ER
M12	HR	HR	HR	HR	HR	MR	ER	HR	MR	HR	HR	HR	HR	HR	ER	HR
M13	ER	ER	HR	ER	HR	HR	HR	ER	HR	HR	HR	MR	ER	ER	MR	ER
M14	ER	HR	ER	ER	HR	ER	MR	ER	ER	ER	ER	ER	ER	ER	HR	ER
M15	HR	HR	HR	HR	HR	HR	ER	ER	HR	HR	HR	HR	ER	HR	HR	ER
M16	ER	HR	HR	HR	ER	MR	MR	ER	ER	HR	ER	HR	ER	ER	LR	ER
M17	ER	ER	HR	ER	HR	HR	ER	ER	ER	MR	ER	ER	ER	HR	ER	HR
M18	HR	HR	HR	HR	HR	HR	MR	HR	HR	HR	HR	HR	HR	HR	HR	MR
M19	ER	ER	ER	MR	HR	MR	ER	ER	HR	MR	MR	MR	HR	HR	MR	HR
M20	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER	ER
M21	HR	HR	ER	HR	ER	ER	ER	ER	HR	HR	MR	HR	LR	HR	MR	HR
M22	HR	HR	ER	HR	MR	ER	MR	HR	HR	HR	HR	HR	HR	HR	HR	HR
M23	HR	HR	HR	HR	MR	MR	LR	HR	HR	HR	HR	ER	LR	MR	MR	HR
M24	ER	ER	ER	ER	HR	MR	LR	MR	ER	LR	HR	HR	LR	LR	HR	MR

E1: Energy Consumption; E2: Energy Usage; E3: Energy Cost; E4: Energy Input; E5: Energy Value; E6: Energy Utilisation; E7: Non-Value-Added Energy; E8: Value-Added Energy; E9: Energy Cost per Item; E10: Energy Consumption per Defective Item; P1: Cycle Time; P2: Lead Time; P3: Greenhouse Gas Emissions; P4: Power Required; P5: Waiting Time; P6: Water Consumption.

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Appendix C. Initial direct relation matrix I – Respondent 1.

	P1	P3	P4	P5	P6
E1	EI	EI	EI	HI	EI
E2	EI	EI	EI	HI	EI
E3	HI	EI	EI	HI	EI
E4	EI	EI	EI	HI	EI
E5	EI	EI	EI	EI	EI
E6	EI	EI	EI	EI	EI
E9	EI	EI	EI	EI	EI
E10	EI	EI	EI	EI	EI

E1: Energy Consumption; E2: Energy Usage; E3: Energy Cost; E4: Energy Input; E5: Energy Value; E6: Energy Utilisation; E9: Energy Cost per Item; E10: Energy Consumption per Defective Item; P1: Cycle Time; P3: Greenhouse Gas Emissions; P4: Power Required; P5: Waiting Time; P6: Water Consumption.

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Appendix D. Triangular Fuzzy numbers (a), Fuzzy defuzzification process (b, c) and direct relation matrix D (d) – Respondent 1.

a		P1			P3			P4			P5			P6	
E1	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.5	0.7	0.9)	(0.7	0.9	1)
E2	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.5	0.7	0.9)	(0.7	0.9	1)
E3	(0.5	0.7	0.9)	(0.7	0.9	1)	(0.7	0.9	1)	(0.5	0.7	0.9)	(0.7	0.9	1)
E4	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.5	0.7	0.9)	(0.7	0.9	1)
E5	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)
E6	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)
E9	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)
E10	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)	(0.7	0.9	1)
b	fl	fm	fr	fl	fm	fr	fl	fm	fr	fl	fm	fr	fl	fm	fr
E1	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0	0	0)	(0	0	0)
E2	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0	0	0)	(0	0	0)
E3	(0	0	0)	(0	0	0)	(0	0	0)	(0	0	0)	(0	0	0)
E4	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0	0	0)	(0	0	0)
E5	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0.4	0.4	0.2)	(0	0	0)
E6	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0.4	0.4	0.2)	(0	0	0)
E9	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0.4	0.4	0.2)	(0	0	0)
E10	(0.4	0.4	0.2)	(0	0	0)	(0	0	0)	(0.4	0.4	0.2)	(0	0	0)
c		lv	rv		lv	rv		lv	rv		lv	rv		lv	rv
E1		0.40	0.25		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00
E2		0.40	0.25		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00
E3		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00
E4		0.40	0.25		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00
E5		0.40	0.25		0.00	0.00		0.00	0.00		0.40	0.25		0.00	0.00
E6		0.40	0.25		0.00	0.00		0.00	0.00		0.40	0.25		0.00	0.00
E9		0.40	0.25		0.00	0.00		0.00	0.00		0.40	0.25		0.00	0.00
E10		0.40	0.25		0.00	0.00		0.00	0.00		0.40	0.25		0.00	0.00
d		x			x			x			x			x	
E1		0.356			0.000			0.000			0.000			0.000	
E2		0.356			0.000			0.000			0.000			0.000	
E3		0.000			0.000			0.000			0.000			0.000	
E4		0.356			0.000			0.000			0.000			0.000	
E5		0.356			0.000			0.000			0.356			0.000	
E6		0.356			0.000			0.000			0.356			0.000	
E9		0.356			0.000			0.000			0.356			0.000	
E10		0.356			0.000			0.000			0.356			0.000	

E1: Energy Consumption; E2: Energy Usage; E3: Energy Cost; E4: Energy Input; E5: Energy Value; E6: Energy Utilisation; E9: Energy Cost per Item; E10: Energy Consumption per Defective Item; P1: Cycle Time; P3: Greenhouse Gas Emissions; P4: Power Required; P5: Waiting Time; P6: Water Consumption.

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Appendix E. Direct relation matrix G for energy metrics on environmental and production process metrics.

	P1	P3	P4	P5	P6
E1	0.254	0.272	0.235	0.189	0.207
E2	0.229	0.230	0.206	0.179	0.173
E3	0.175	0.200	0.191	0.163	0.162
E4	0.125	0.231	0.205	0.137	0.114
E5	0.175	0.229	0.189	0.210	0.185
E6	0.257	0.275	0.197	0.292	0.207
E9	0.223	0.225	0.211	0.246	0.183
E10	0.152	0.169	0.152	0.230	0.181

E1: Energy Consumption; E2: Energy Usage; E3: Energy Cost; E4: Energy Input; E5: Energy Value; E6: Energy Utilisation; E9: Energy Cost per Item; E10: Energy Consumption per Defective Item; P1: Cycle Time; P3: Greenhouse Gas Emissions; P4: Power Required; P5: Waiting Time; P6: Water Consumption.