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Text mining-based categorization and user perspective analysis of environmental sustainability indicators for manufacturing and service systems

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ABSTRACT

In response to increasing global consciousness about the environmental impact of companies, a wide variety of environmental sustainability indicators and frameworks have been developed. Despite the variety of available environmental sustainability indicators, the absence of a commonly accepted categorization framework often creates confusion and inhibits indicator deployment in practice. This paper addresses this issue with a bottom-up approach that categorizes environmental sustainability indicators using their text-based objective information, and investigates industrial perceptions on indicator use. As the foundation for this work, 55 environmental sustainability indicators were extracted from extant literature. Then, companies from manufacturing and service domain were surveyed to reveal perceptions on utilization status (i.e. used in practice and future implementation) and utility (i.e. usefulness and practicality) of each indicator. For indicator categorization, the text descriptions of the collected indicators were modeled using a text mining technique, the correlated topic model, to extract their latent topics as a basis to categorize the indicators. As a result, five categories and their relevant indicators were defined. Further, the utilization status and utility levels of the indicators within the derived categories were analyzed. Possible relationships between indicator utility levels and company characteristics were also identified through logistic regression. Utility levels of specific indicators were found to change subject to market location and industry sector. Findings from this study can complement top-down conceptual categorization and inform implementation of indicators.

1. Introduction

Environmental sustainability is a broad concept that involves all scales of activities and efforts to maintain the appropriate quality of environmental infrastructure for short-term and long-term human well-being (Goodland, 1995; Moldan et al., 2012). Environmental sustainability has become an important issue for companies as their activities have been linked to a significant portion of global environment problems; for example, total global greenhouse gas emissions for industry and waste/wastewater increased by nearly 50% between 1990 and 2010, and 47% of wastewater produced in industrial sectors is untreated (IPCC, 2014). Given increasing global awareness towards environmental issues, companies are now urged to minimize their negative environmental impacts caused throughout the whole life-cycles of manufacturing processes, products, and services (Gunasekaran and Spalanzani, 2012; Klassen and McLaughlin, 1996; Yang et al., 2011). Moreover, business environments with limited natural resource capacity, energy cost fluctuation, environmental regulations, stakeholders' requirements, and cleaner technologies drive firms to integrate environmental sustainability in their core business strategies (Albino et al., 2009; Albino et al., 2012); thus, environmental sustainability is increasingly recognized as a new path of corporate competiveness (Dangelico and Pujari, 2010; Leonidou et al., 2015; Rao and Holt, 2005; Sonntag, 2000). Indeed, successful environmental management in firms leads to positive financial performance (Klassen and McLaughlin, 1996; Leonidou et al., 2015; Wong et al., 2012); and companies can attract environment-friendly customers through proactive efforts to satisfy environmental regulations and to reduce their environmental impacts (Bacallan, 2000; Martín-Peña et al., 2014).

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As a response to the emergence of environmental sustainability as a core business strategy and societal responsibility, a large number of indicators, indices, and accompanying assessment frameworks have been developed to assess progress and shortcomings towards environmental sustainability (Jasch, 2000; Joung et al., 2013; Singh et al., 2012). Indicators for environmental sustainability, as basic assessors of environmental impacts, have served a vital role. They utilize terms and values to effectively represent the multifaceted nature of environmental sustainability that can otherwise seem complex and ambiguous (Niemeijer and de Groot, 2008; Pannell and Glenn, 2000). Environmental sustainability indicators can be distinguished from metrics. Indicators effectively characterize various states of observed systems for decision makers to target and monitor environmental performance in firms (Jasch, 2000), whereas metrics are often used as means and measurements in calculating indicators (Veleva and Ellenbecker, 2001). Various indicators have been selectively grouped as indicator sets or aggregated as indices to provide assessment frameworks to comprehensively cover different aspects of environmental sustainability (Singh et al., 2012).

Despite the availability of various environmental sustainability indicators and assessment frameworks, it is still difficult for companies to use environmental sustainability indicators in practice. Companies face challenges in selecting a specific operational subset of indicators for their products and processes (Joung et al., 2013). Companies need to understand the relevance and potential benefits of numerous indicators to their objectives on environmental sustainability management in order to monitor their progress appropriately. They also should be able to properly organize applicable indicators in multiple environmental areas for a comprehensive interpretation of environmental impacts. Although evaluation frameworks with indicator sets or indices in extant literature support indicator selection, they often rely on ad hoc categorization and selection of indicators that may cause insufficient or excessive coverage across indicator categories. Moreover, the lack of information with regards to the utility of indicators and the technical and theoretical orientation of indicators hamper their implementation in practice.

Noting the necessity of indicator categorization and selection through an objective process that reflects users' perspectives, this paper focuses on environmental sustainability indicators for manufacturing and service systems to provide: 1) a logical decision process for categorizing indicators, 2) indicator utilization status and perceived utility levels in companies, and 3) an analysis of indicator utility subject to company characteristics. The remainder of this paper is organized into five sections. Section 2 reviews previous research on categorization and selection of environmental sustainability indicators. Section 3 introduces the preliminary work on the identification of available environmental sustainability indicators and the company surveys conducted to discern their utilization status and perceived utility levels. Section 4 presents an approach to categorize the collected environmental sustainability indicators through text mining along with its results. Section 5 presents the indicator survey results for the derived categories and analyzes the indicator utility levels and company characteristics through logistic regressions to reveal associations. Section 6 summarizes this work and proposes a compact set of useful and practical indicators for industrial use.

2. Previous research on categorization and selection of sustainability indicators

Indicator sets and indices combining various sustainability dimensions or areas help companies to measure their sustainability efforts on a much larger scale in comparison to the use of individual indicators (Joung et al., 2013). Indicator sets and indices can be used to conduct an unbiased evaluation of sustainability performance to easily identify deficit areas requiring further improvement. Responding to the necessity of sustainability evaluation from a holistic view, many studies have proposed indicator sets and indices that cover multifaceted sustainability dimensions from product/process, organizational, and regional perspectives. They include many indicators that can be employed to measure companies' sustainability efforts.

Earlier studies mainly focused on the development of indicator sets and indices relevant to environmental sustainability. Krotscheck and Narodoslawsky (1996) proposed the Sustainable Process Index (SPI), which consists of indicators to measure the areas required to provide raw materials and energy demands, to accommodate processes for products and by-products in a sustainable way. Shane and Graedel (2000) determined 10 categories of urban environmental sustainability for the essential components of cities and a representative indicator for each category to evaluate the sustainability levels of cities. Esty et al. (2005) of the Yale Center for Environmental Law and Policy developed the Environmental Sustainability Index (ESI) to assess environmental sustainability in regions and countries. ESI consists of 21 environmental sustainability indicators and categorizes these indicators into five core components derived from a broad theoretical basis in the ecological sciences and environmental policy.

Several of the frameworks featured categories of indicators covering environmental, social, and economic sustainability aspects. For example, Veleva and Ellenbecker (2001) proposed a framework with 22 core indicators for six indicator categories to facilitate measuring progress towards sustainable production in companies; this framework considers environmental, social, and economic aspects of an organization's activities. Schmidt and Taylor (2006) proposed the Product Sustainability Index (PSI), consisting of eight sustainability indicators in the environmental, social, and economic categories, to perform a life-cycle assessment in automotive products development. The United Nations' Department of Economic and Social Affairs (UN, 2007) provided 96 indicators grouped by 14 economic, social, and environmental health themes to measure the level of sustainable development in countries and regions.

Some frameworks were designed to be more relevant to various functional areas or foci in companies. The Organisation for Economic Co-operation and Development (OECD, 2011) introduced 18 key sustainable manufacturing indicators categorized by inputs, operations, and products to provide a sustainable manufacturing tool-kit for the evaluation of environmental performance in manufacturing companies. Erol et al. (2011) developed a sustainability assessment framework enabling multi-criteria sustainability evaluation for supply chains and determined a set of 37 indicators within environmental, social, and economic sustainability for retail companies. Efroymson and Dale (2015) provided an indicator set for analyzing the sustainability of algal biofuels, which consists of 16 environmental indicators in six categories to represent environmental sustainability areas for bioenergy.

A logical and clear process for categorizing and selecting indicators is required to ensure effectiveness and reliability of indicator use. Accordingly, methodological approaches to establish guidelines for proper indicator categorization and selection have been also discussed in the literature. Pannell and Glenn (2000) developed a conceptual framework based on Bayesian decision theory for the economic valuation and prioritization of sustainability indicators in agriculture to facilitate indicator selection under uncertain decision making environments. Krajnc and Glavič (2005) proposed a decision framework to create a composite sustainable development index for measuring and comparing performance of companies in all dimensions of sustainability, which can select, group, and aggregate indicators with different units and measurement characteristics through a series of heuristic and mathematical steps. Niemeijer and de Groot (2008) provided a conceptual framework for environmental indicator selection through a causal network to identify interrelationships and similarities between indicators for a specific domain. Feng and Joung (2009) and Feng et al. (2010) investigated a performance measurement infrastructure for sustainable manufacturing and proposed an indicator repository that contains a comprehensive set of available sustainable indicators; the indicator hierarchies of this repository reflect associated categories and product life-cycle stages of indicators. Lin et al. (2012) provided a conceptual model for environmental indicator selection and quantitatively formulated an indicator selection problem through integer programming and genetic algorithm. Joung et al. (2013) reviewed available sustainability indicator sets for manufacturing and categorized them based on their similarities in five dimensions of sustainability: environmental stewardship, economic growth, social well-being, technological advancement, and performance management.

Overall, the extant studies in categorization and selection of sustainability indicators can be divided into two types: top-down and bottom-up (Singh et al., 2012). The majority of the studies utilize a top-down approach, which pre-defines sustainability criteria or categories in a framework according to theoretical and technical meanings and then allocates indicators in each category based on their perceived theoretical similarities. This approach can theoretically cover a comprehensive spectrum of indicators and provide well-defined indicator categories. However, it often results in redundant and ambiguous indicators across categories due to the subjective and ad hoc assignment of sustainability indicators into categories. Also, theoretically oriented sustainability frameworks often include less useful and less practical indicators due mostly to the lack of consideration for indicator utility in practice.

To overcome these challenges, a bottom-up approach that creates categories from available indicator information and provides an analysis of the levels of utilization and perceived utility for each indicator is useful. Similarities between indicators identified through objective information (i.e. documented descriptions) can help derive appropriate categories. Also, information on indicator utilization and perceived utility obtained from surveys in various industrial companies effectively supports the decision making process for indicator selection. This bottom-up approach can complement the prevailing ad hoc categorization of indicators from top-down approaches. Moreover, sustainability indicators selected based on their perceived utility can support a company's transition to indicator deployment for monitoring progress towards increased sustainability.

3. Collection and survey of environmental sustainability indicators

Sustainability in manufacturing and service industry refers to the creation of manufactured products and services with processes and systems that are non-polluting, conserving of energy and natural resources, safe for employees and communities, and economically sound (Centenera and Hasan, 2014; DOC, 2008; Veleva and Ellenbecker, 2001). The definition of sustainable manufacturing and service encompasses three dimensions of sustainability (i.e. environmental, economic, and social) in line with the general consensus on the dimensions of sustainability in other domains (Gunasekaran and Spalanzani, 2012; Haapala et al., 2013). This study is focused on environmental sustainability in manufacturing and service companies, where environmental issues are regarded as intense (Haapala et al., 2013; Kassinis and Soteriou, 2003). As an extension of the preliminary work from Park and Kremer (2013), this section provides a comprehensive set of environmental sustainability indicators, that can be used to measure progress towards environmentally sustainable manufacturing and service systems. Their utilization status and utility levels are also captured through a survey instrument that was completed by professionals in various companies.

3.1. Identification of environmental sustainability indicators

There is no one widely agreed upon definition for an indicator, and it has been defined in various ways in the literature (Joung et al., 2013; Singh et al., 2012; Veleva and Ellenbecker, 2001). Gallopin (1997) investigated the various definitions of the term "indicator" and concluded that an indicator should be regarded as a variable representing a specific attribute in a system. Similar to this definition, Joung et al. (2013) defined an indicator as "a measure or an aggregation of measures from which conclusions on the phenomenon of interest can be inferred." This research adopts the definition of Joung et al. (2013) for an indicator to extract environmental sustainability indicators from the literature.

A variety of sources were collected, from journal papers to books and other published reports, to compile environmental sustainability indicators and review them. 47 papers and other works were examined; and indicators in these sources that relate to environmental impact measurements, production specification, energy, and raw materials in production, distribution, and service processes were extracted to create a comprehensive list. Each indicator was characterized with the following attributes:

- Identification (ID): the unique abbreviated identifier of an indicator
- Name: the title to represent an indicator
- Definition: the statement that describes essential characteristics of an indicator
- Life Cycle (LC) Category: the product life-cycle stage that is associated with an indicator
- Simplified Formula: the simplified equation to derive the value of an indicator
- Formula Terms: the description of each formula term
- References: the documents from which an indicator is found or referred to

Indicators in various sources tend to be described with different terms although they have similar conceptual meanings. Therefore, the collected indicators were redefined by using common terms to eliminate any confusion resulting from a different representation of the same term. For this, major publications which clearly provide quantified and descriptive indicators were found. Then, all the original sources containing similar terms, definitions, and formulas for each pre-identified indicator were sorted. After the information for each indicator was identified from all of the original sources, the definitions and associated formulas of key terms in each indicator were populated in rows of a matrix. Once all the sources were studied and recorded in the matrix of indicators, each indicator was reanalyzed to streamline the information included and to consolidate similar indicators. Through this refinement process, the key concepts and components of each indicator were examined; the description of each indicator was redefined with common terms, and the quantitative formula and variables for each indicator were transformed to mathematically simplify the measurement. Notably, each variable in the indicator formulas was identically defined across indicators to avoid the use of tautological variables. In all the cases where formulas were nonexistent or different for the same indicator, the most appropriate and clarified quantification method was included. Indicators with limited or no information were dismissed during the consolidation process. From the above refinement steps, 55 indicators were identified as a comprehensive environmental sustainability indicator set for manufacturing and service systems. The detailed information for this resultant indicator set is specified in Appendix A.

3.2. Survey on utilization and utility of environmental sustainability indicators

Proper adoption and implementation of environmental sustainability indicators are important in manufacturing and service systems to facilitate a transition to environmentally sustainable systems. From this point of view, the identified indicators in the previous section should be reviewed from users' perspectives. A survey instrument was developed and sent to 288 companies from the U.S., France, and Taiwan, with global manufacturing and distribution centers, to evaluate the refined list of indicators using four criteria (See Table 1).

In addition to providing utilization and perceived utility information per indicator, all company representatives who participated in the survey were asked to record basic information about their companies (i.e. main industry sector, location of major markets, and company size). The survey results returned from 82 companies were combined to construct a dataset for analysis, and records with missing values were deleted from the dataset. As a result, 79 companies' responses (US: 59, France: 8, and Taiwan: 12) were used. Fig. 1 shows a subset of the dataset.

Based on the datasets constructed as summarized in Sections 3.1 and 3.2, the following sections address the logical categorization of the comprehensive indicator set and the analysis of the collected utilization and utility information.

4. Categorization of environmental sustainability indicators

This section proposes a text mining approach using the text descriptions of indicators to logically categorize indicators based on their conceptual similarities.

4.1. Topic model and text representation

The text descriptions of the indicators organized in Section 3.1 can be used to objectively identify similarities between the indicators. With the collected text information for each indicator, a text mining approach based on machine learning algorithms and natural language processing techniques can effectively extract underlying patterns in the text descriptions. Among various methods in text mining, this paper focuses on a topic model (Blei and Lafferty, 2007; Blei et al., 2003), that has emerged as a useful tool for categorizing large sets of documents, as a basis for indicator categorization.

Topic models provide probabilistic modeling of term frequencies in a corpus (Hornik and Grün, 2011), which is a collection of text documents. Topic models can be employed to extract latent topics in a corpus and also to identify similarities between documents. Topic models have been applied to a wide variety of application areas for non-text processing such as image processing (Fei-Fei and Perona, 2005), network data modeling (Airoldi et al., 2007), and geographical information retrieval (Li et al., 2008) as well as text-based information processing such as abstract-reference relations (Erosheva et al., 2004) and author-document relations (Rosen-Zvi et al., 2004).

A representative topic model is the Latent Dirichlet Allocation (LDA) model proposed by Blei et al. (2003). This model assumes that the occurrences of words in each document are originated by a mixture of latent topics, where each topic is multinomial over a fixed set of words and follows its own distribution over words. The latent topics are shared by each document with a distinct topic distribution since the topics are randomly drawn from a Dirichlet distribution. The Correlated Topic Model (CTM), developed by Blei and Lafferty (2007), is an extended version of the LDA model. Topics in the LDA model are assumed to be uncorrelated to each other. However, subsets of underlying latent topics in documents can be correlated since it is often observed that a document is associated with several similar topics. Considering correlations among latent topics, the CTM method replaces the Dirichlet distribution of the LDA model with a more flexible distribution, the logistic normal distribution, to provide a realistic topic model.

Documents in topic models are represented by a group of words referred to as the bag-of-words model. The bag-of-words model assumes that the order of words in a document has no impact on retrieving information (Baeza-Yates and Ribeiro-Neto, 1999). Through the bag-of-words representation, each document is transformed to a vector representing its associated words and their frequencies as seen in Eq. (1) (Huang, 2008).

$$\vec{t}_d = (f(d,t_1), \cdots, f(d,t_m)) \tag{1}$$

where $D = \{d_1, \cdots, d_n\}$: a set of documents, $T = \{t_1, \cdots, t_m\}$: a set of terms in D, $\vec{t}_d$: an m-dimensional vector to describe a document, and $f(d,t)$: the frequency of a term ($t \in T$) in a document ($d \in D$).

Terms extracted for the bag-of-words model indicate descriptive words appearing in a set of documents. There are several steps to obtain analyzable terms from all words used in documents for text data analysis (Andrews and Fox, 2007). First, non-descriptive words (e.g. a, the, and is), which are called stop-words, are excluded from the set of terms. Also, words with the same stem are treated as a single word. It is assumed that the words stemmed from the same root inherently deliver the same meaning in text.

Common terms frequently appearing in a small number of documents can be treated to be more important in analyzing relevant documents than terms occurring in every document (Robertson, 2004). To reflect this property, each term frequency can be inversely weighted according to its occurrence in a set of documents and transformed into the Term Frequency–Inverse Document Frequency (TF-IDF) as shown in Eq. 2 (Salton and Buckley, 1988).

$$f(d,t)^* = f(d,t) \times \log(n/n_t) \tag{2}$$

where n is the number of all documents, and n_t is the number of documents having t.

4.2. Methodology for indicator categorization through topic model

The following steps are performed to derive topic-based categories for the indicators from their text information.

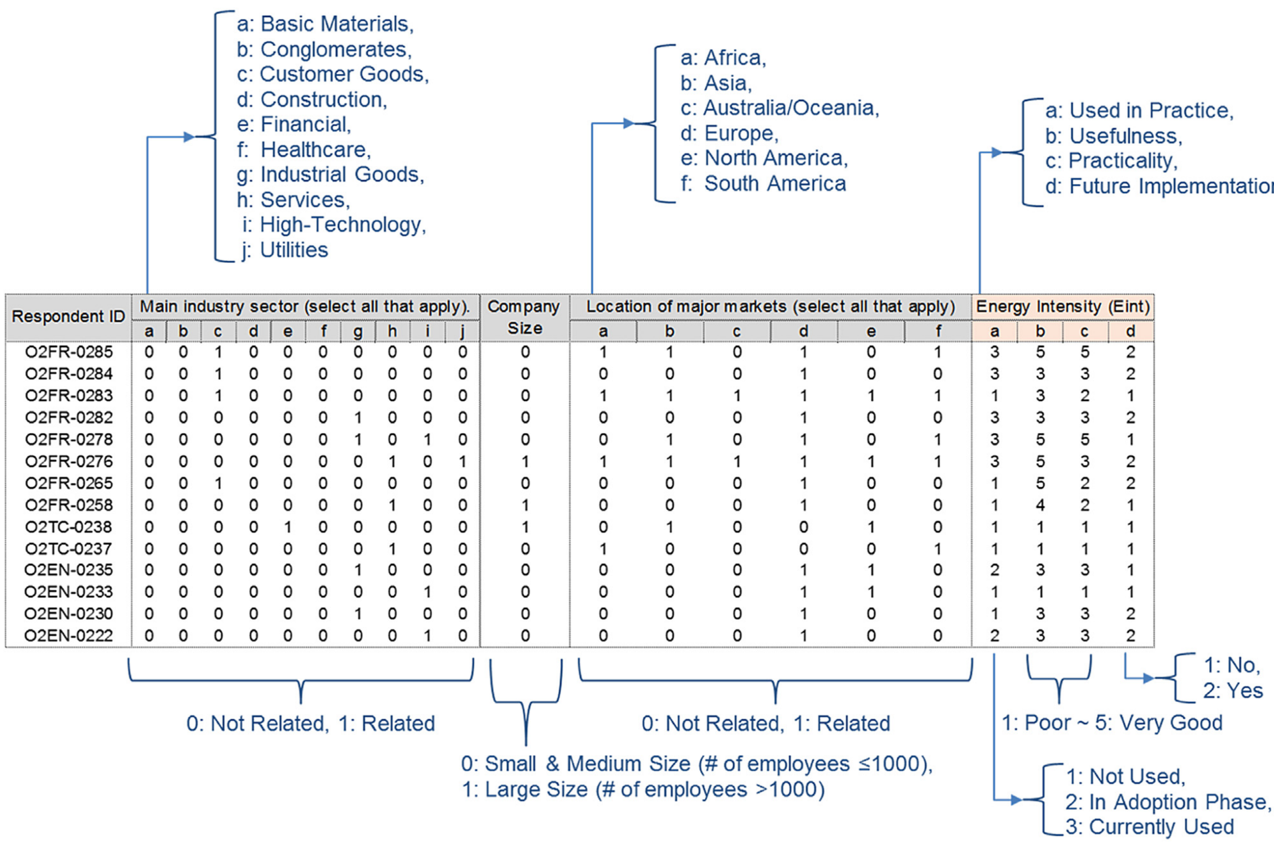
4.2.1. Pre-processing of text data

The indicator information except references from the table in Appendix A is used as text inputs for analysis. First of all, each row in the description table for the indicators is separately stored into a "txt" file. Then, the tm package (Feinerer and Hornik, 2015) for the R statistical programming language (R, 2015) is used to construct a corpus of the indicator text data and to remove stop words and whitespaces in the corpus; and each word in the indicator corpus is stemmed using the SnowballC (Bouchet-Valat, 2014) package.

After organizing and refining the indicator corpus, it is exported to a document-term matrix. Very infrequent terms, also called sparse terms, of the indicators can become a noise factor while driving topics; thus, those sparse terms in the document-term matrix are removed. The TF-IDF values of all terms are calculated to omit terms that very frequently appear across the indicators. Terms having a TF-IDF value less than the first quartile of the calculated TF-IDF values are excluded to build a better fitted topic model.

Table 1
Evaluation Criteria for Environmental Sustainability Indicators.

Main Criteria	Sub-Criteria	Description	Input Values
Utilization: Current and future usage of an indicator	Used in Practice	Current usage status of an indicator	1: Not Used, 2: In Adoption Phase, 3: Currently Used
	Future Implementation	Likelihood of implementing an indicator in the future	1: No, 2: Yes
Utility: Inherent value and feasibility of an indicator	Usefulness	Perceived economic and operational value of an indicator	1–5, with 5 being the most useful
	Practicality	Perceived cost and time to learn and to implement an indicator	1–5, with 5 being the most practical



Respondent ID	Main industry sector (select all that apply).										Company Size	Location of major markets (select all that apply)						Energy Intensity (Eint)			
	a	b	c	d	e	f	g	h	i	j		a	b	c	d	e	f	a	b	c	d
O2FR-0285	0	0	1	0	0	0	0	0	0	0	0	1	1	0	1	0	1	3	5	5	2
O2FR-0284	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	3	3	2
O2FR-0283	0	0	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	3	2	1
O2FR-0282	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	3	3	3	2
O2FR-0278	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	1	3	5	5	1
O2FR-0276	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	3	5	3	2
O2FR-0265	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	5	2	2
O2FR-0258	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	1	4	2	1
O2TC-0238	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	1	0	1	1	1	1
O2TC-0237	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	1	1	1	1
O2EN-0235	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	2	3	3	1
O2EN-0233	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1	1	1	1
O2EN-0230	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	3	3	2
O2EN-0222	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	2	3	3	2

Fig. 1. Sample Dataset of Indicator Utilization and Utility for Energy Intensity Indicator.

4.2.2. Implementation of CTM

Using the above described pre-processing procedure, a final document-term matrix is prepared to fit a topic model. The CTM method is employed because latent topics describing the indicators are assumed to be highly correlated. The topic models package included in the tm package (Feinerer and Hornik, 2015) is used to fit a CTM.

Six categories – energy, water, resources, pollution, environment, and technique/process – were derived according to the compiled indicator definitions of the indicators during the preliminary work on the categorization of the indicators (Park and Kremer, 2013). Based on this information, the number of topics for a fitted indicator topic model is initially set as six to verify the previous ad hoc categorization. Then, the CTM is redone by increasing or decreasing the number of topics from six to find a better solution, depending on the result of the fitted CTM.

4.2.3. Topic-based indicator categorization

Each topic derived from a fitted CTM is interpreted with its frequently occurring terms to define an indicator category. The most likely topic for each indicator is obtained to identify the indicators associated with each topic.

4.3. Results

The indicator corpus originally had 345 words to describe 55 indicators. These words were reduced to 257 terms after removing stop words and stemming each word in the corpus. The frequency of each term in the corpus and its graphical representation are shown in Fig. 2. The word cloud in Fig. 2 provides terms occurring more than three times in the indicator descriptions, where terms with bigger font sizes indicate more frequently occurring terms. The histogram for terms over frequency of 20 in Fig. 2 shows a quick visual overview of the frequency of terms in the indicator set. In the original indicator corpus, “use- (e.g. use, used, and useful),” and “number- (e.g. number),” “manufactur- (e.g. manufacturing)” are the three most frequent terms, and “mass- (e.g. mass),” “resource- (e.g. resource and resources),” “volum- (e.g. volume),” “wast- (e.g. waste and wastes),” “product- (e.g. product, productivity, and production),” “water- (e.g. water),” and “energi- (e.g. energy)” also

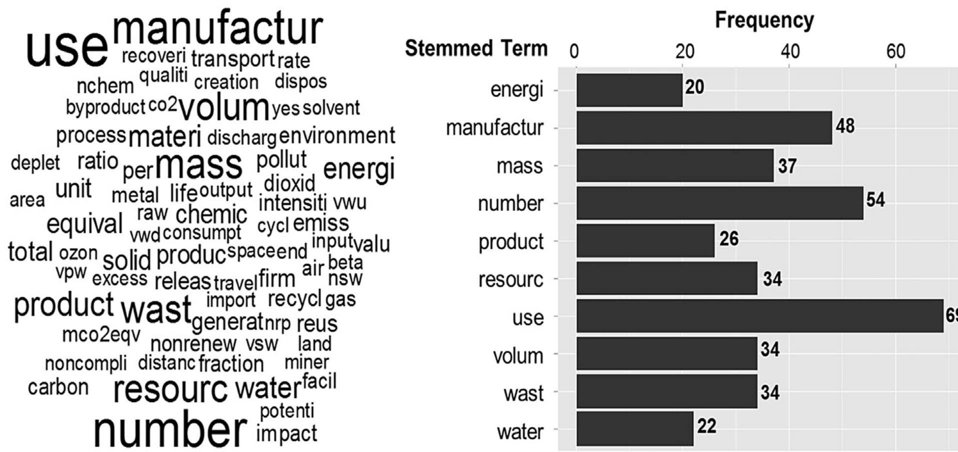


Fig. 2. Word Cloud (Left) and Histogram (Right) of Term Frequency for Indicators.

Table 2
Top Eight Frequent Terms in Document-Term Matrix with Reduced Vocabulary.

Stemmed Term (/Original Words)	Frequency
"resourc" (/resource and resources)	34
"wast" (/waste and wasted)	34
"product" (/product, productivity, and production)	26
"water" (/water)	22
"energi" (/energy)	20
"materi" (/material, materials)	19
"solid" (/solid)	17
"equival" (/equivalents)	16

frequently appear over 20 times in the indicator set. These frequent terms suggest that most indicators relate to measurements focusing on resource use and disposal in different environmental areas for manufacturing.

Infrequent terms do not significantly contribute to the categorization of the indicators, and they can cause confusion in deriving latent topics. To prevent this confusion, terms having 95% of sparsity (i.e. that are not associated with 95% of all the indicators) were eliminated from the document-term matrix. Very frequent terms observed across a majority of the indicators do not play a significant role in distinguishing latent topics for indicators either. Thus, only terms having more than the first quartile value of TF-IDF (=0.2906) were included in the document-term matrix to omit frequently occurring terms in most indicators. Finally, 40 terms for 55 indicators in the original indicator corpus and their frequencies were extracted to construct the document-term matrix for fitting a topic model. Table 2 shows the terms occurring more than 15 times in the document-term matrix with a reduced vocabulary, and these terms are regarded as terms frequently appearing in each specific subset of the indicators.

Initially, six categories were created by sorting 55 indicators into groups where each indicator is believed to be most relevant (see Table 3). A CTM with six topics was built on the pre-processed document-term matrix to see how the initial categorization can be changed. Table 4 shows resultant six topics, the five most frequent terms for each topic, and each indicator's most likely topic obtained from the fitted CTM solution.

The derived topics in Table 4 show a more logical basis for the categorization of 55 indicators than the ad hoc categorization shown in Table 3. For example, CO2 (Carbon Dioxide Emissions) and CF (Carbon Footprint) are similar in that they are associated with carbon-related emissions, but they were separately assigned to Pollution and Environment through the initial ad hoc categorization. On the other hand, the fitted CTM resulted in grouping these indicators in the same topic.

Table 3
Initial Categorization of 55 Indicators.

Category	Indicators
Energy	EEI (Excess Energy Intensity), EInt (Energy Intensity), EU (Energy Use), LCEInt (Life Cycle Energy Intensity), NREU (Non-Renewable Energy Use), and TEInt (Transportation Energy Intensity)
Water	CWI (Core Water Intensity), EUT (Eutrophication), WDI (Water Discharge Intensity), WInt (Water Intensity), WP (Water Pollution), WQ (Water Quality), and WU (Water Usage)
Resources	CU (Chemicals Used), EI (Environmental Impact), FUtil (Facility Utilization), IP (Import Percentage), LU (Land Use), MR (Mineral Reserves Used), MU (Material Use), NRRC (Non- Renewable Resource Consumption), OSU (Organic Solvent Usage), RC (Resource Consumption), RE (Resource Efficiency), RP (Resource Productivity), RRS (Rate of Resource Sustainability), RS (Resource Sustainability), RU (Resource Use), and TD (Travel Distance)
Pollution	AP (Air Pollution), BP (Byproducts Produced), CO2 (Carbon Dioxide Emissions), PSW (Percent of Solid Waste), RM (Recyclability Rate for Metals), RRR (Recycling/Reuse Rate), SW (Solid Waste), SWRR (Solid Waste Reuse Rate), TE (Transportation Emission per Unit), WC (Waste Chemicals), WG (Waste Generation), and WUtil (Waste Utilization)
Environment	ACP (Acidification Potential), CF (Carbon Footprint), CInt (Carbon Intensity), ET (Ecological Toxicity), GGE (Greenhouse Gas Emissions), OCP (Photochemical Ozone Creation Potential), OZ (Ozone Depletion), and PPD (Pollution Plume Dispersion)
Technique/Process	β (Value Ratio for a Firm), EE (Eco-Efficiency), EOLR (End of Life Recovery Process), LPT (Lean Production Techniques), PLE (Product Life Extension), and RNC (Regulatory Non-Compliance)

The six topic-CTM shows that Topic 6 is associated with only one indicator. This implies that a decrease in the number of topics to five might have a better CTM fit. Moreover, the duplication of frequently appearing terms in Topic 3, Topic 4, and Topic 6 can hamper clear separation among these topics. For these reasons, a five topic-CTM under the same conditions as with the previous six-topic CTM was conducted. The result shows that each indicator has its own most likely topic among five topics (See Table 5). The derived five topics form more balanced indicator subsets; and these topics can be considered as main themes and categories for the indicators. The topics derived from the 5 topic-CTM are interpreted based on the estimated frequent terms of the topics as follows.

Table 4
Result of CTM with Six Topics.

Topics	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6
Frequent Stemmed Terms (/Original Words)	"equival" (/equivalents)	"wast" (/waste and wastes)	"chemic" (/chemicals and chemical)	"resourc" (/resource and resources)	"water" (/water)	"energi" (/energy)
	"releas" (/released)	"solid" (/solid)	"life" (/life)	"materi" (/material and materials)	"emiss" (/emissions)	"product" (/product, products, production, and productivity)
	"firm" (/firm)	"unit" (/unit, units)	"nchem" (/ N_{Chem})	"product" (/product, products, production, and productivity)	"pollut" (/pollution, pollutant, and polluted)	"qualiti" (/quality)
	"environment" (/environment and environmental)	"produc" (/produced)	"end" (/end)	"recycl" (/recycle, recyclability, recycling, and recycled)	"gas" (/gas and gases)	"life" (/life)
	"valu" (/value)	"generat" (/generated)	"product" (/product, products, production, and productivity)	"facil" (/facility)	"vwu" (/ V_{WU})	"produc" (/produced)
Indicators	ACP, β, CF, CInt, CO2, EE, EI, ET, EUT, LU, OCP, OZ, and RRS	BP, EEI, EInt, PSW, SW, SWRR, TE, TEInt, WG, WDI, and WUtil	CU, EOLR, LCEInt, LPT, OSU, PLE, RM, and WC	FUtil, IP, MR, MU, NREU, NRRC, RC, RE, RNC, RP, RRR, RS, RU, and TD	AP, CWI, GGE, PPD, WInt, WP, WQ, and WU	EU

Table 5
Result of CTM with Five Topics.

Topics	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Frequent Stemmed Terms (/Original Words)	"equival" (/equivalents)	"wast" (/waste and wastes)	"chemic" (/chemicals and chemical)	"resourc" (/resource and resources)	"water" (/water)
	"releas" (/released)	"solid" (/solid)	"life" (/life)	"materi" (/material and materials)	"energi" (/energy)
	"firm" (/firm)	"generat" (/generated)	"product" (/product, products, production, and productivity)	"product" (/product, products, production, and productivity)	"unit" (/unit, units)
	"environment" (/environment and environmental)	"emiss" (/emissions)	"end" (/end)	"facil" (/facility)	"produc" (/produced)
	"valu" (/value)	"pollut" (/pollution, pollutant, and polluted)	"nchem" (/ N_{Chem})	"raw" (/raw)	"vwu" (/ V_{WU})
Indicators	ACP, β, CF, CInt, CO2, EE, EI, ET, EUT, LU, OCP, OZ, and RRS	AP, BP, GGE, PPD, PSW, SW, SWRR, TE, WG, and WUtil	CU, EOLR, LCEInt, LPT, OSU, PLE, RM, and WC	FUtil, IP, MR, MU, NRRC, RC, RE, RNC, RP, RRR, RS, and TD	CWI, EEI, EInt, EU, NREU, RU, TEInt, WDI, WInt, WP, WQ, and WU

- Category 1 (Topic 1): environmental impact and chemical release related indicators
- Category 2 (Topic 2): pollution from emissions and wastes related indicators
- Category 3 (Topic 3): end of life management and chemicals usage related indicators
- Category 4 (Topic 4): raw materials and facility management related indicators
- Category 5 (Topic 5): energy and water management related indicators

5. Utilization and utility analysis of environmental sustainability indicators

This section analyzes the current utilization and perceived utility of the environmental indicators in companies, obtained from the survey study described in Section 3.2. The survey results are summarized in Section 5.1. Section 5.2 employs logistic regression to investigate the changes in the utility levels subject to company characteristics.

5.1. Survey results on utilization and utility of indicators

From the utilization aspect of the identified 55 environmental sustainability indicators, the average number fraction of companies that currently use each environmental sustainability indicator in practice or are in its adoption phase is 33.4%. On the other hand, the average number fraction of companies that are likely to implement each environmental sustainability indicator in the future is 50.2%. This indicates that companies recognize the importance of implementing environmental sustainability indicators in their business although almost two-thirds do not use environmental sustainability indicators currently.

The indicators are rated with the overall average 3.05 out of 5 in usefulness and 2.87 out of 5 in practicality. This shows that the indicators are perceived to be fairly valuable for companies, but lack in practicality for adoption in practice. For usefulness, EU (Energy Use) is the most useful indicator (= average 3.65), and β (value ratio for a firm) is perceived as the least useful indicator (= average 2.46). For practicality, EU is still regarded as the best indicator (= average 3.51), OCP (photochemical Ozone Creation Potential) is the least practical indicator (= average 2.32). The indicator evaluation results

Table 6
Summary of Used in Practice Results by Category.

Category	Overall Average	Indicator with Highest Number Fraction	Indicator with Lowest Number Fraction
1	29.4%	CO2 (46.8%)	EUT (20.3%)
2	30.4%	AP and SW (39.2%)	TE (21.5%)
3	35.0%	LPT (50.6%)	RM (25.3%)
4	38.4%	MU (51.9%)	MR (24.1%)
5	34.3%	EU (54.4%)	WInt (19.0%)

Table 7
Summary of Results on Future Implementation by Category.

Category	Overall Average	Indicator with Highest Number Fraction	Indicator with Lowest Number Fraction
1	44.9%	CF and CO2 (55.7%)	ACP and OCP (35.4%)
2	48.5%	WG (59.5%)	PPD (35.4%)
3	51.6%	LPT (65.8%)	EOLR, PLE, and WC (46.8%)
4	54.5%	MU and RRR (64.6%)	MR (41.8%)
5	52.1%	EU (74.7%)	WInt (35.4%)

Table 8
Summary of Usefulness Results by Category.

Category	Overall Average	Indicator with Highest Average	Indicator with Lowest Average
1	2.91	CF (3.58)	β (2.46)
2	2.99	GGE (3.30)	PPD (2.78)
3	3.04	LPT (3.44)	OSU (2.76)
4	3.17	RRR (3.57)	MR (2.66)
5	3.13	EU (3.65)	WDI (2.80)

Table 9
Summary of Practicality Results by Category: Average Practicality Level.

Category	Overall Average	Indicator with Highest Average	Indicator with Lowest Average
1	2.71	CF (3.39)	OCP (2.32)
2	2.82	AP (3.16)	PPD (2.48)
3	2.81	CU (3.20)	PLE (2.41)
4	3.07	MU (3.34)	MR (2.73)
5	2.91	EU (3.51)	WInt (2.51)

for the derived indicator categories are stated in the following subsections.

5.1.1. Used in practice

Category 4 shows the highest average number fraction of the surveyed companies in the adoption or implementation phase of the indicators within the category, and Category 1 is identified as the least utilized indicator group (See Table 6).

As seen in Table 6 and Fig. 3, the indicators currently implemented or in adoption by over 50% of the surveyed companies are EU, LPT (Lean Production Techniques), and MU (Material Use). These indicators are straightforward to be understood and implemented, and companies can employ them without calculations through complex indicator formulas; for example, through monitoring electric consumption at a workstation (e.g. EU), simple Yes or No evaluation (e.g. LPT), and counting the number of different materials used (e.g. MU). These properties make them accessible to companies. On the other hand, the indicators with the lowest number fraction in the indicator categories are measurements requiring specific devices and knowledge of data collection to be employed in companies.

5.1.2. Future implementation

Table 7 and Fig. 4 show the number fraction of companies planning the future implementation of each indicator. EU, LPT, and MU, which each average over 50% for the "Used in Practice" criterion, are also being considered for implementation in the future. This consistent result shows that an effective environmental sustainability assessment framework can be built based on these indicators. The high number fractions of the EU, LPT, and MU indicators show that the surveyed companies seem to recognize the importance of energy, waste, and material management. The indicators with the lowest future implementation likelihood are those deemed difficult to measure (e.g. OZ: OZone depletion, WC: Waste Chemicals, and WInt: Water Waste Intensity), requiring a large scale inspection (e.g. ACP: ACidification Potential, OCP, and PPD: Pollution Plume Dispersion), supported with expert knowledge and skills (e.g. EOLR: End of Life Recovery and PLE: Product Life Extension), and involving specific resources (e.g. MR: Mineral Reserves).

5.1.3. Usefulness

Category 4 shows the highest average level in usefulness among the indicator categories (See Table 8 and Fig. 5). This indicates that the surveyed companies put more value on raw materials, production, and facility management related indicators in practice. In contrast, the average level of Category 1 is the lowest. It includes the indicators related to environmental impact (e.g. β, EE: Eco-Efficiency, and EI: Environmental Impact) and regional air/water quality measured through chemical releases (e.g. ACP, EUT: EUTrophication, OCP), resulting in low usefulness (See Fig. 5). The indicators included in Category 1 partly require companies to have their own judgment on the environmental impact of their activities and to grow capability to keep track of specific chemical releases. Thus, the indicators that involve in-depth understanding of environmental impact and are not directly related to major interests tend to be perceived as less valuable in the surveyed companies for their environmental sustainability management.

The indicator with the highest average level in each category shows that its value in achieving environmental sustainability in manufacturing and service systems is evaluated more highly over other indicators within the same category. The foci of these indicators are related to carbon footprint (e.g. CF: Carbon Footprint), greenhouse gases (e.g. GGE: Greenhouse Gas Emission), lean production to minimize wastes (e.g. LPT), recycled and reused raw materials (e.g. RRR: Recycling/Reuse Rate), and energy usage (e.g. EU). On the other hand, the indicators with the lowest average level in their categories are based on economic value of a firm (e.g. β), air pollutant dispersion (e.g. PPD), specific solvent and mineral usage (e.g. OSU: Organic Solvent Usage and MR), and water discharge (e.g. WDI: Water Discharge Intensity).

5.1.4. Practicality

All the categories have an average level in practicality relatively lower than that in usefulness (See Table 9 and Fig. 6). Notably, most categories have an average level with less than three points, which means that the indicators within each category are regarded as somewhat impractical on average. In line with the results of indicator usefulness, Category 4 and Category 1 show the highest average level and the lowest average level among all the categories, respectively. The lowest average level of Category 1 seems to occur due to difficulties to quantify and measure the associated indicators. EU is the most practical indicator among all the indicators as it is identified as the most useful indicator.

The indicators perceived to be the most practical in their relevant categories focus on mass of pollutant gas emissions (e.g. CF and AP: Air Pollution) and usage of chemicals, energy, and raw materials (e.g. CU, EU, and MU). On the other hand, the indicators that require comprehensive examination of regional water and air pollution (e.g. OCP, PPD, and WInt), product life-cycle based analysis

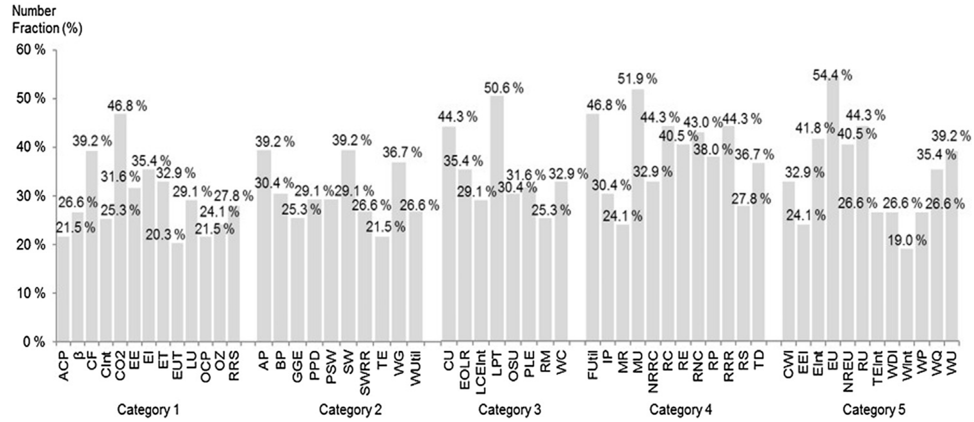


Fig. 3. Used in Practice Status for Each Indicator.

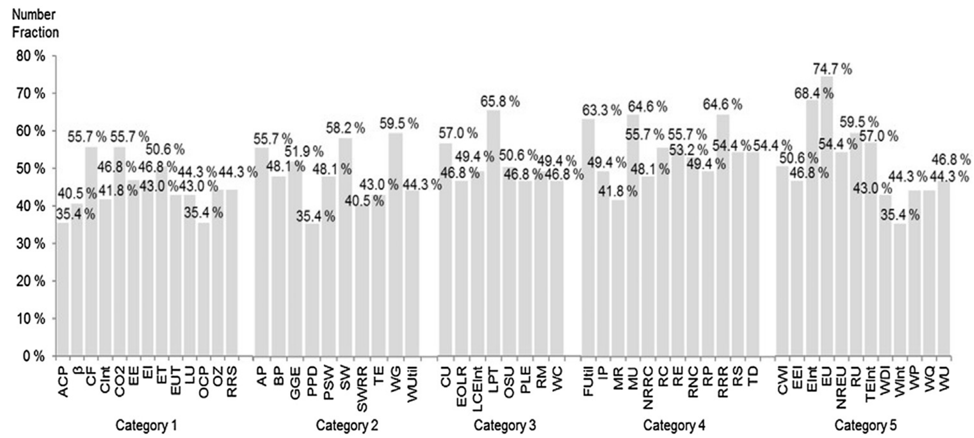


Fig. 4. Future Implementation Likelihood for Each Indicator.

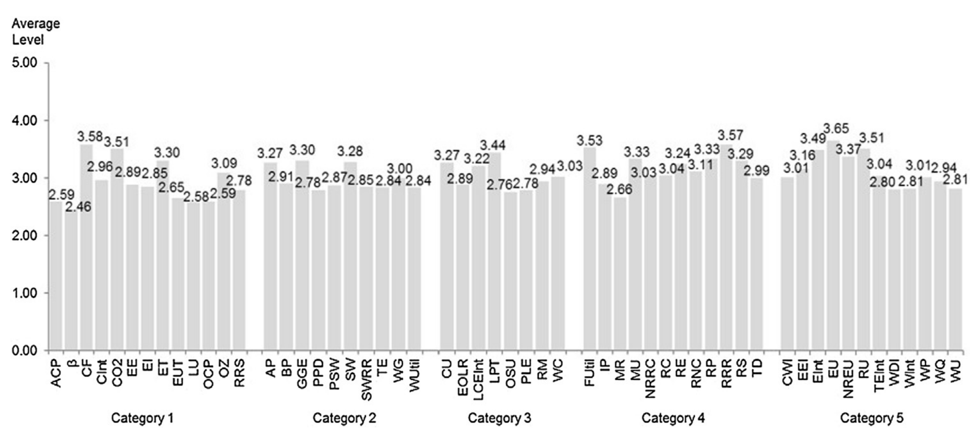


Fig. 5. Average Usefulness Rating for Each Indicator.

(e.g. PLE: Product Life Extension), and tracking mineral usage (e.g. MR) turn out to be the least practical in their categories.

5.2. Relationships between perceived indicator utility and company characteristics

The perceived indicator utility might depend on certain characteristics of a company. For example, companies in a specific industry sector often perceive environmental sustainability indicators that are closely related to their industry as more useful or practical than those for other industry sectors. Therefore, salient relationships between perceived indicator utility and company characteristics should be identified in order to develop a set of utilitarian environmental sustainability indicators customized for specific company characteristics.

The relationships between indicator utility levels and company characteristics are identified by logistic regressions in the following subsections. The goal is to see how company characteristics influence the most useful or practical indicator in each category. The logistic regression is appropriate for the analysis because it is suitable for relationship mining between predictor variables and a categorical or an ordinal response variable (Hosmer and Lemeshow,

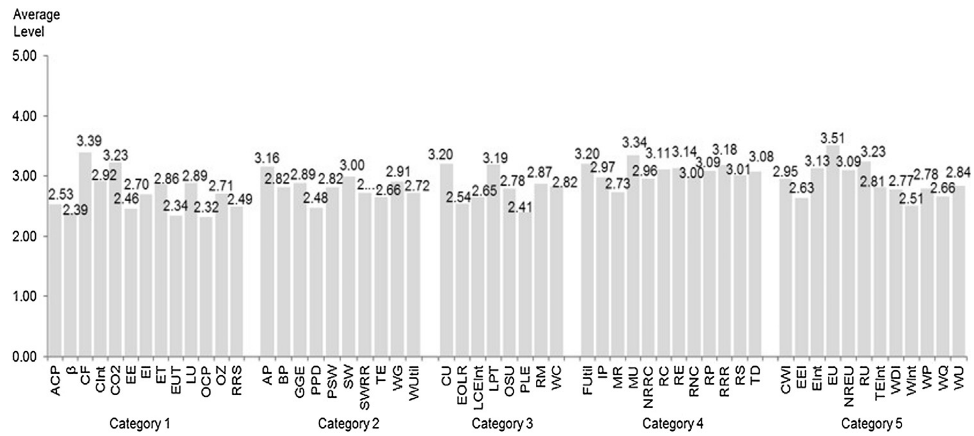


Fig. 6. Average Practicality Rating for Each Indicator.

2000). The background information of the surveyed companies (i.e. main industry sector, company size, and location of major market) summarized in Section 3.2 is employed as fixed predictor variables for each logistic regression model. As for response variables, the perceived usefulness and practicality of the indicator that has the highest average level in each indicator category are respectively used. Thus, a total of ten multiple logistic regression models were built using the software package MINITAB. Since the primary purpose of the logistic regression analysis is not to derive a predictive model for indicator utility, but to identify the relationships between indicator utility and company characteristics, the statistical significance of predictor variables and relevant interpretation in each logistic regression model are mainly considered for analysis.

5.2.1. Relationships between usefulness and company characteristics

Table 10 shows the main parameters (i.e. C: coefficient, P: *p*-value, O: odds ratio) of each company characteristic variable in the logistic regression models with each category's most useful indicator. Indicators with less than 0.05 in the *p*-values of predictors are regarded as those that have significant relationships with company characteristics, and the odds ratio of a statistically significant predictor shows the ratio between the two binary groups of the predictor in the odds of lower utility levels versus higher utility levels.

The significant positive coefficient and the odds ratio value of "Construction" in the logistic regression model for the usefulness of RRR indicate that companies associated with the construction industry tend to perceive lower usefulness levels of RRR than companies in other sectors. The odds of having lower usefulness levels compared to higher usefulness levels in RRR for companies in the construction industry are 25.97 times greater than for companies in other industry sectors, with all other variables constant. This result is at odds with the current consensus that the construction industry should show efforts to reduce its huge raw material consumption through reuse and recycling of waste construction materials (Vefago and Avellaneda, 2013). The fact that none of the surveyed construction companies use RRR in current practice explains that they might not see reuse and recycling of materials for environmentally sustainable construction as a priority.

The "High-Technology" variable of GGE in Table 10 has a significant negative coefficient and an odds ratio value less than 1; this shows that the mentioned variable is associated with higher levels of indicator usefulness. The odds of lower usefulness levels versus higher usefulness levels in GGE for companies in the high-technology industry are 0.22 times lower than companies in other industries, keeping all other variables constant. This indicates that companies in the high-technology industry are likely to evaluate GGE with higher usefulness levels than companies in other industry sectors. Recent industrial efforts to reduce greenhouse gases through development of green technologies (e.g. green computing and electric vehicles) might explain the positive relationship between GGE and its usefulness.

Similarly, the significant negative coefficient and odds ratio of RRR show that companies with European markets can be related with higher usefulness in RRR than companies with other regional markets. This result indicates that RRR can be considered as more useful in companies with European markets, regardless of their industry types. Possible regional effects to impacting the underlying value of RRR are environmental regulations/policies and customer awareness about recycle and reuse in European markets.

5.2.2. Relationships between practicality and company characteristics

Table 11 shows that the location of major markets can affect companies' perceived practicality levels of CU, and the industry type can be related to the practicality of MU.

The significant negative coefficient and odds ratio of the "Europe" variable in the logistic regression model for the practicality of CU show that companies with European markets can be related with higher practicality in CU than companies with other regional markets. This result indicates that the implementation of CU can be effectively encouraged in companies with European markets.

The positive coefficients and the odds ratio values of the significant variables in the logistic regression model with MU indicate that companies in the construction, industrial goods, finance, and services related industry tend to have lower practicality levels of MU. MU provides the number of different types of raw materials used. In comparison to other companies, companies in the construction sector and the industrial goods sector regard MU to be less practical; this might be due to the fact that companies involving construction and industrial goods commonly use a wide variety of raw materials in their business processes. Also, companies in the financial industry and the service industry might put lower value on the practicality of MU due to difficulties in defining and tracking raw materials that are used in their business processes.

6. Discussion and conclusions

This paper presents an innovative approach to indicator categorization and analyzes the utilization and utility of environmental sustainability indicators through available indicators for environmental sustainability in manufacturing and service systems. The

Table 10
Logistic Regression Results for Usefulness and Company Characteristics.

Company Characteristics (Predictors)	Most Useful Indicator in Each Category (Response)														
	Category 1: CF			Category 2: GGE			Category 3: LPT			Category 4: RRR			Category 5: EU		
	C	P	O	C	P	O	C	P	O	C	P	O	C	P	O
1.Main Industry Sector															
a. Basic Materials	0.12	0.89	1.13	−0.59	0.50	0.56	−0.21	0.81	0.81	−0.71	0.46	0.49	0.16	0.86	1.17
b. Conglomerates	−1.63	0.35	0.20	−10003	0.98	0.00	−1.93	0.31	0.14	−2.04	0.34	0.13	−10002	0.98	0.00
c. Consumer Goods	−0.60	0.49	0.55	−0.65	0.45	0.52	0.41	0.64	1.51	1.16	0.20	3.18	−0.72	0.43	0.49
d. Construction	0.61	0.59	1.84	0.74	0.58	2.10	2.21	0.08	9.12	**3.26**	**0.02**	**25.97**	0.33	0.79	1.38
e. Financial	10002	0.98	∞	10002	0.98	∞	2.16	0.17	8.66	2.97	0.07	19.51	0.68	0.66	1.97
f. Healthcare	−20002	0.97	0.00	−20002	0.97	0.00	−10002	0.98	0.00	−10001	0.98	0.00	−10001	0.98	0.00
g. Industrial Goods	−0.87	0.19	0.42	−1.03	0.13	0.36	0.13	0.86	1.14	0.76	0.28	2.14	−0.20	0.78	0.82
h. Services	−0.16	0.84	0.85	−0.86	0.31	0.42	1.45	0.11	4.26	1.15	0.19	3.16	0.00	1.00	1
i. High-Technology	−0.49	0.48	0.61	**−1.53**	**0.04**	**0.22**	0.89	0.23	2.43	1.02	0.16	2.79	−0.19	0.80	0.83
j. Utilities	−10002	0.98	0.00	−10003	0.98	0.00	1.17	0.49	3.22	1.12	0.48	3.07	1.65	0.31	5.2
2. Size	−0.83	0.15	0.44	−0.89	0.13	0.41	0.07	0.90	1.08	−0.19	0.74	0.83	−0.35	0.54	0.71
3. Location of Major Markets															
a. Africa	−0.48	0.42	0.62	0.23	0.70	1.26	−0.43	0.46	0.65	−1.10	0.08	0.33	−1.13	0.07	0.32
b. Asia	−0.18	0.72	0.84	−0.95	0.06	0.39	−0.59	0.23	0.55	−0.33	0.51	0.72	−0.34	0.49	0.71
c. Australia/Oceania	1.16	0.26	3.18	1.74	0.11	5.69	−2.15	0.07	0.12	0.18	0.86	1.20	−0.57	0.62	0.57
d. Europe	−0.36	0.49	0.70	−0.99	0.07	0.37	−0.49	0.35	0.61	**−1.24**	**0.02**	**0.29**	−0.68	0.20	0.5
e. North America	0.33	0.53	1.40	0.57	0.29	1.78	−0.04	0.93	0.96	−0.05	0.93	0.95	0.58	0.28	1.79
f. South America	0.40	0.54	1.49	0.85	0.21	2.33	0.45	0.49	1.57	0.58	0.39	1.78	−0.20	0.76	0.82

Note: C (coefficient), P (*p*-value), O (odds ratio), and significant values ($p < 0.05$) in bold text.

Table 11
Logistic Regression Results between Practicality and Company Characteristics.

Company Characteristics (Predictors)	Most Practical Indicator in Each Category (Response)														
	Category 1: CF			Category 2: AP			Category 3: CU			Category 4: MU			Category 5: EU		
	C	P	O	C	P	O	C	P	O	C	P	O	C	P	O
1.Main Industry															
a. Basic Materials	−0.41	0.64	0.67	0.73	0.45	2.07	−0.97	0.28	0.38	0.46	0.62	1.58	0.78	0.38	2.18
b. Conglomerates	−1.90	0.31	0.15	−10002	0.97	0.00	−10001	0.98	0.00	−2.58	0.22	0.08	−2.44	0.18	0.09
c. Consumer Goods	0.66	0.45	1.93	−0.28	0.75	0.75	0.41	0.64	1.51	0.88	0.33	2.40	−0.29	0.75	0.75
d. Construction	1.14	0.32	3.13	10002	0.97	∞	1.79	0.17	5.98	**4.02**	**0.01**	**55.62**	1.69	0.17	5.40
e. Financial	10003	0.98	∞	1.62	0.32	5.07	1.87	0.23	6.51	**3.94**	**0.02**	**51.53**	1.76	0.26	5.83
f. Healthcare	−10002	0.98	0.00	−0.05	0.99	0.95	−2.94	0.27	0.05	−4.48	0.10	0.01	−10001	0.98	0.00
g. Industrial Goods	−0.37	0.59	0.69	−1.19	0.09	0.30	0.87	0.20	2.38	**1.84**	**0.01**	**6.32**	−0.27	0.70	0.76
h. Services	0.73	0.39	2.07	−0.13	0.88	0.88	0.75	0.37	2.11	**3.02**	**0.00**	**20.44**	−0.15	0.86	0.86
i. High-Technology	−0.65	0.37	0.52	−0.95	0.19	0.39	0.26	0.71	1.30	0.93	0.21	2.54	−0.36	0.63	0.70
j. Utilities	1.39	0.38	4.01	−0.20	0.90	0.82	0.15	0.92	1.17	1.39	0.39	4.01	2.38	0.14	10.85
2. Size	−0.64	0.26	0.53	−0.85	0.14	0.43	−0.36	0.52	0.70	−0.25	0.66	0.78	−0.16	0.78	0.86
3. Location of Major Markets															
a. Africa	−0.45	0.44	0.64	0.13	0.82	1.14	−0.94	0.11	0.39	−0.32	0.59	0.73	−0.53	0.36	0.59
b. Asia	−0.74	0.14	0.48	−0.88	0.08	0.41	−0.62	0.21	0.54	−0.91	0.08	0.40	−0.80	0.11	0.45
c. Australia/Oceania	−0.73	0.49	0.48	0.24	0.81	1.28	1.22	0.24	3.40	−0.17	0.88	0.85	−0.07	0.95	0.93
d. Europe	−0.44	0.40	0.65	−0.57	0.29	0.56	**−1.29**	**0.02**	**0.28**	−0.97	0.07	0.38	−0.64	0.22	0.53
e. North America	−0.64	0.23	0.53	0.33	0.53	1.39	0.05	0.93	1.05	0.46	0.39	1.59	0.24	0.65	1.27
f. South America	0.68	0.30	1.97	0.56	0.39	1.75	0.43	0.51	1.54	−0.76	0.25	0.47	−0.64	0.34	0.53

Note: C (coefficient), P (*p*-value), O (odds ratio), and significant values ($p < 0.05$) in bold text.

primary approach of the indicator categorization is a bottom-up process, which extracts available indicators from an extensive review of literature and then categorizes them through their conceptual similarities. Furthermore, this paper focuses on understanding indicators in each derived category from user perspectives represented by the utilization and utility of indicators.

Using 55 indicators obtained from an extensive review of the literature, the text descriptions of the indicators were used to derive their latent topics through CTM. The derived topics for the indicators served as a basis to categorize the indicators; five categories were defined with their relevant indicators. This text mining-based indicator categorization process complements the prevailing top-down approach in indicator categorization since conceptual similarities between indicators can be objectively integrated into indicator categorization.

The utilization status and perceived utility levels of 55 indicators that were collected through surveys from professionals in manufacturing and service systems were further analyzed. The purpose of the indicator utilization and utility analysis is to provide guidance to decision makers in selecting indicators. The average number fraction of the surveyed companies that currently use or are adopting each indicator is 33.4%; and 50.2% of the companies revealed the planned future implementation of each indicator on average. The increase in the overall average rate supports that manufacturing and service companies hope to further facilitate environmental sustainability management through the increase in the number of implemented indicators. It also indicates, however, almost half of the companies will not employ many environmental sustainability indicators; the usefulness and practicality of the indicators can be major issues impacting this decision. Of all 55 indicators, EU was perceived by companies as the most useful and practical indicator, but β and OCP were rated as the least useful indicators and the least practical indicators, respectively.

It is also found that utility levels of some specific indicators tend to vary based on the industry sectors and major market locations of companies. This implies that the utility of the associated indicators can be related to business types and regional policy differences. From this point of view, indicators can be selectively organized to create an evaluation framework for corporate environmental sustainability by considering the industry sectors and market locations of companies. A flexible indicator set, which can be customized according to industry sectors and market locations, would be more effective to facilitate the implementation of indicators in companies.

The usefulness and practicality of each indicator can be employed for companies to support their indicator selection decisions. Table 12 shows 18 indicators that are perceived as satisfying at least the average utility level (≥ 3) in both usefulness and practicality. These indicators can be considered as a concise set of useful and practical environmental indicators for companies that is helpful to facilitate monitoring and managing corporate activities impacting on environment. According to companies' foci with regards to environmental sustainability, indicators in different categories can be selectively extracted to develop a valuable and practical framework for environmental sustainability assessment. An effective indicator selection process, which enables decision makers to reflect their preferences and perceived thresholds in indicator usefulness and practicality, would be helpful to choose the most appropriate indicators for the compact indicator set.

Development of environmental sustainability indicators should be considered with their expected value and practicality in practice. For example, most valuable and practical indicators are associated with Category 4 and Category 5. Indicators in other categories should be revised by setting more clear descriptions and effective measurement methods. Also, all the indicators except MU and RC in Table 12 have a usefulness level greater than their practicality level.

Table 12
Useful and Practical Environmental Sustainability Indicator Set.

Indicator (Abbreviation)	Average Usefulness Level	Average Practicality Level	Indicator Category
Energy Use (EU)	3.65	3.51	Category 5
Carbon Footprint (CF)	3.58	3.39	Category 1
Resource Use (RU)	3.51	3.23	Category 5
Carbon Dioxide Emissions (CO2)	3.51	3.23	Category 1
Recycling/Reuse Rate (RRR)	3.57	3.18	Category 4
Facility Utilization (FUtil)	3.53	3.20	Category 4
Material Use (MU)	3.33	3.34	Category 4
Lean Production Techniques (LPT)	3.44	3.19	Category 3
Energy Intensity (EInt)	3.49	3.13	Category 5
Chemical Use (CU)	3.27	3.20	Category 3
Non-Renewable Energy Use (NREU)	3.37	3.09	Category 5
Air pollution (AP)	3.27	3.16	Category 2
Resource Productivity (RP)	3.33	3.09	Category 4
Resource Efficiency (RE)	3.24	3.14	Category 4
Resource Sustainability (RS)	3.29	3.01	Category 4
Solid Waste (SW)	3.28	3.00	Category 2
Resource Consumption (RC)	3.04	3.11	Category 4
Regulatory Non-Compliance (RNC)	3.11	3.00	Category 4

This implies that useful environmental sustainability indicators should be improved to be more practical indicators for manufacturing and service companies. Furthermore, underlying relationships between indicators and perceived indicator utility should be investigated to identify what components and properties in indicators can affect indicator utility and how an indicator should be constructed to achieve a desired usefulness and practicality level in practice.

The bottom-up approach for the categorization and analysis of environmental sustainability indicators addressed in this paper can support development of effective indicators and assessment frameworks for industrial practice. Although only the environmental dimension of sustainability is considered in this paper, the indicator categorization process and analysis of indicator utilization and utility can be extended to the whole spectrum of sustainability for manufacturing and service systems in future work. Indicators of economic, social, and environmental sustainability that can be practically employed and provide value for manufacturing and service systems would be extracted to construct an integrated sustainability indicator repository. The proposed indicator categorization in this paper would facilitate an effective organization within the indicator repository, which enables manufacturing and service companies to access a comprehensive set of sustainability indicators with ease and clarity. Furthermore, utilization and utility information collected and analyzed for each indicator in the repository would support the indicator selection process.

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Appendix A. : Comprehensive indicator set for environmnetally sustainable systems

ID	Name	Definition	LC Category	Simplified Formula	Formula Term		References
					Variable	Unit	
ACP	Acidification Potential	Mass of regional air quality through kg of SO_2 (sulfur dioxide) gas equivalents	Manufacturing	$\Sigma m_{SO2\text{-}eqv}$	$m_{SO2\text{-}eqv}$ = Mass of sulfur dioxide equivalents released	kg	(Labuschagne and Brent, 2005)
AP	Air Pollution	Mass fraction of air pollutant gas emissions to total gas emissions	Manufacturing	$\Sigma m_{PE}/\Sigma m_{GE} \times 100$	m_{PE} = mass of pollutant gas emissions m_{GE} = mass of total gas emissions	kg kg	(Jin and High, 2004)
β	Value Ratio for a Firm	Value created by a firm per reference firm value	Manufacturing	V_C/V_{Ref}	V_C = value creation (revenue) by a firm V_{Ref} = reference firm value (average contribution to GDP by firms)	$/a $/a	(Mosovsky et al., 2000)
BP	Byproducts Produced	Number of total byproducts and wastes generated	Manufacturing	ΣN_{BP}	N_{BP} = number of byproducts and wastes generated in a process	1	(Linton et al., 2007)
CF	Carbon Footprint	Mass of total CO_2 (carbon dioxide) and other greenhouse gases, emitted over the full life cycle of a process	Manufacturing	$\Sigma m_{CO2\text{-}eqv}$	$m_{CO2\text{-}eqv}$ = carbon dioxide equivalents released	kg	(Hertwich and Peters, 2009; Matthews et al., 2008)
CInt	Carbon Intensity	Mass of CO_2 (carbon dioxide) equivalents released per energy used	Manufacturing	$\Sigma m_{CO2\text{-}eqv}/\Sigma E_U$	$m_{CO2\text{-}eqv}$ = carbon dioxide equivalents released E_U = energy used	kg kW h	(EIA, 2013)
CO2	Carbon Dioxide Emissions	Mass of CO_2 (carbon dioxide) equivalents released by processes	Manufacturing	$\Sigma m_{CO2\text{-}eqv}$	$m_{CO2\text{-}eqv}$ = carbon dioxide equivalents released	kg	(Linton et al., 2007; Nagurney et al., 2007; Petrie et al., 2007; Wang and Lin, 2004)
CU	Chemicals Used	Number of chemicals used in processes	Manufacturing	ΣN_{Chem}	N_{Chem} = number of chemicals used	1	(Sikdar, 2007)
CWI	Core Water Intensity	Volume of water used per number of units produced	Manufacturing	$\Sigma V_{WU}/\Sigma N_Q$	V_{WU} = volume of water used N_Q = number of units produced	m^3 1	(NRTEE, 2001)
EE	Eco-Efficiency	Value ratio per environmental impact of a firm	Manufacturing	β/I (=1/I^*)	β = value ratio for a firm I = ratio of environmental impact I^* = ratio of adjusted environmental impact	1 1 1	(Mosovsky et al., 2000)
EEI	Excess Energy Intensity	Total excess energy generated during manufacturing processes	Manufacturing	ΣE_{EXC}	E_{EXC} = excess energy generated	kW h	(NRTEE, 2001)
EI	Environmental Impact	Sum of environmental impacts from supply and output aspects	Manufacturing	$\Sigma I_S + \Sigma I_O$	I_S = ratio of environmental impact of raw materials and supplied resources I_O = ratio of environmental impact of produced materials and wastes	1 1	(Mosovsky et al., 2000)
EInt	Energy Intensity	Total energy used per units produced	Manufacturing	$\Sigma E_U/\Sigma N_Q$	E_U = energy used, N_Q = number of units produced	kW h 1	(Mosovsky et al., 2000; NRTEE, 2001; Sikdar, 2003)
EOLR	End of Life Recovery Process	Is a clear end of life recovery process to recycle and reuse wastes defined?	End of Life Disposal	*Yes or No*	–	–	(Linton et al., 2007)
ET	Ecological Toxicity	Mass of Pb equivalents that have toxicity potentials to humans or animals	Manufacturing	$\Sigma m_{Pb\text{-}eqv}$	$m_{Pb\text{-}eqv}$ = Pb equivalents released	kg	(Labuschagne and Brent, 2005; Wang and Lin, 2004)
EU	Energy Use	Energy used during manufacturing processes	Manufacturing	ΣE_U	E_U = energy used	kW h	(Gaughran et al., 2007; Martins et al., 2007; Naidu et al., 2008; Rachuri et al., 2009; Wilson et al., 2007)
EUT	Eutrophication	Mass of PO_4 equivalents that can cause eutrophication in water	Manufacturing	$\Sigma m_{PO4\text{-}eqv}$	$m_{PO4\text{-}eqv}$ = PO_4 equivalents released	kg	(Labuschagne and Brent, 2005)

FUtil	Facility Utilization	Area fraction of facility space used for production in total facility space	Manufacturing	$\Sigma A_{UF}/\Sigma A_F \times 100$	A_{UF} = area of facility used	m^2	(Lavy et al., 2014; Lee and Lee, 2002; Zhou et al., 2000)
					A_F = area of total facility space	m^2	
GGE	Greenhouse Gas Emissions	Mass of anthropogenic emissions of CO_2, CH_4, N_2O, HFCs, PFCs, SF_6, CFCs, HCFC5, NO, CO, and NMVOCs	Manufacturing	Σm_G	m_G = Mass of all emissions combined from these gases	kg	(Eggleston et al., 2006; Thomas et al., 2000; Wang and Lin, 2004)
IP	Import Percentage	Number fraction of raw materials imported from outside	Raw Materials	$\Sigma N_{IR}/\Sigma N_{RP} \times 100$	N_{IR} = number of imported resources	1	(Albino et al., 2002)
					N_{RP} = number of resources used on products	1	
LCEInt	Life Cycle Energy Intensity	All energy used during all phases of a product life cycle	All Phases	ΣE_{LC}	E_{LC} = energy used throughout a product life cycle	kW h	(NRTEE, 2001)
LPT	Lean Production Techniques	Are lean and quality control techniques used to minimize wastes?	Manufacturing	*Yes* or *No*	–	–	(Linton et al., 2007)
LU	Land Use	Area of land used by a particular firm for production	Manufacturing	ΣA_L	A_L = area of land used, occupied, or transformed by corporation	m^2	(Labuschagne and Brent, 2005; Wang and Lin, 2004)
MR	Mineral Reserves Used	Mass of minerals used	Raw Materials	$\Sigma m_{Coal\text{-}eqv}$	$m_{Coal\text{-}eqv}$ = coal equivalents used	kg	(Labuschagne and Brent, 2005)
MU	Material Use	Number of different types of raw materials used	Manufacturing	ΣN_{MU}	N_{MU} = number of materials used	1	(Ijomah et al., 2007; Martins et al., 2007)
NREU	Non-Renewable Energy Use	Energy used through gas, petroleum, electricity, coal, or other non-renewable resources	Manufacturing	ΣE_{NREU}	E_{NREU} = energy used through non-renewable resources	kW h	(Albino et al., 2002; Labuschagne and Brent, 2005; Petrie et al., 2007; Wang and Lin, 2004)
NRRC	Non-Renewable Resource Consumption	Number (or volume, or mass) fraction of non-renewable resources used	Manufacturing	$\Sigma N_{NR}/\Sigma N_R \times 100$ (or $\Sigma V_{NR}/\Sigma V_R \times 100$, or $\Sigma m_{NR}/\Sigma m_R \times 100$)	N_{NR} = number of non-renewable resources used	1	(Zhou et al., 2000)
					N_R = number of resources used	1	
					V_{NR} = volume of non-renewable resources used	m^3	
					V_R = volume of resources used	m^3	
					m_{NR} = mass of non-renewable resources used	kg	
					m_R = mass of resources used	kg	
OCP	Photochemical Ozone Creation Potential	Mass of O_3 (ozone) equivalents to measure regional air quality	Manufacturing	$\Sigma m_{O3\text{-}eqv}$	$m_{O3\text{-}eqv}$ = O_3 equivalents released	kg	(Labuschagne and Brent, 2005)
OSU	Organic Solvent Usage	Number fraction of organic solvents used and all chemicals used	Manufacturing	$\Sigma N_{OC}/\Sigma N_{Chem} \times 100$	N_{OC} = number of organic solvents or chemicals used	1	(Sikdar, 2007)
					N_{Chem} = number of chemicals used	1	
OZ	Ozone Depletion	Number of chemicals used with ozone depleting potential or mass of CFC-11 equivalents released	Manufacturing	ΣN_{OZ} or $\Sigma m_{CFC11\text{-}eqv}$	N_{OZ} = number of ozone depleting chemicals used	1	(Labuschagne and Brent, 2005; Linton et al., 2007)
					$m_{CFC11\text{-}eqv}$ = mass of CFC-11 equivalents released	kg	
PLE	Product Life Extension	Is there a way to extend the life of the product once its initial life is over?	End of Life Disposal	*Yes* or *No*	–	–	(Linton et al., 2007)
PPD	Pollution Plume Dispersion	Number of people exposed to air pollutant emissions	Manufacturing	ΣN_P	N_P = number of people exposed to air pollution	1	(Petrie et al., 2007)
PSW	Percent of Solid Waste	Number (or volume) ratio of solid waste and solid use	Manufacturing	$\Sigma N_{SW}/\Sigma N_{SU}$ (or $\Sigma V_{SW}/\Sigma V_{SU}$)	N_{SW} = number of total solid wastes	1	(Albino et al., 2002; Atlee and Kirchain, 2006; Kainuma and Tawara, 2006; Martins et al., 2007; Nam, 2008; Wang and Lin, 2004)
					N_{SU} = number of total solid used	1	
					V_{SW} = volume of total solid wastes	m^3	
					V_{SU} = number of total solid used	m^3	

RC	Resource Consumption	Number (or volume, or mass) of materials (e.g. minerals, and metals, primary, and recycled resources) used to make products and packaging	Manufacturing	ΣN_R (or ΣV_R, or Σm_R)	N_R = number of resources used V_R = volume of resources used m_R = mass of resources used	1 m^3 kg	(Albino et al., 2002; Petrie et al., 2007; Wang and Lin, 2004; Zhou et al., 2000)
RE	Resource Efficiency	Number (or volume, or mass) ratio of useful material output and material input	Manufacturing	$\Sigma N_{UMO}/\Sigma N_{MI}$ (or $\Sigma V_{UMO}/\Sigma V_{MI}$, or $\Sigma m_{UMO}/\Sigma m_{MI}$)	N_{UMO} = number of useful material outputs, N_{MI} = number of material inputs V_{UMO} = volume of useful material outputs V_{MI} = number of material inputs m_{UMO} = mass of useful material outputs m_{MI} = mass of material inputs	1 1 m^3 m^3 kg kg	(Nam, 2008)
RM	Recyclability Rate for Metals	Volume (or mass) ratio of metal used in a product that is purely recycled	End of Life Disposal	$\Sigma V_{MR}/\Sigma V_M$ (or $\Sigma m_{MR}/\Sigma m_M$)	V_{MR} = volume of metals recycled V_M = volume of metal used in production m_{MR} = mass of metals recycled m_M = mass of metal used in production	m^3 m^3 kg kg	(Sikdar, 2007)
RNC	Regulatory Non-Compliance	Number of citations or non-compliance incidents that have occurred at a given facility	Manufacturing	ΣN_{NI}	N_{NI} = number of noncompliance incidents	1	(Wang and Lin, 2004)
RP	Resource Productivity	Production rate per environment impact	Manufacturing	P/I	P = production rate I = environmental impact	1/d 1	(Mosovsky et al., 2000)
RRR	Recycling/ Reuse Rate	Number (or volume, or mass) fraction of resource recovery involving collection and treatment of a waste product for use as a raw material	Manufacturing	$\Sigma N_{RR}/\Sigma N_R \times 100$ (or $\Sigma V_{RR}/\Sigma V_R \times 100$, or $\Sigma m_{RR}/\Sigma m_R \times 100$)	N_{RR} = number of reused or recycled resources N_R = number of resources used V_{RR} = volume of reused or recycled resources V_R = volume of resources used, m_{RR} = mass of reused or recycled resources m_R = mass of resources used	1 1 m^3 m^3 kg kg	(Ijomah et al., 2007; Linton et al., 2007; Wang and Lin, 2004; Zhou et al., 2000)
RRS	Rate of Resource Sustainability	Environmental cost per value creation by a firm	Manufacturing	$\Sigma C_E/\Sigma V_C$	C_E = environmental cost V_C = value creation by a firm	\$/a \$/a	(UNESCAP, 2009)
RS	Resource Sustainability	Average resource availability for products	Manufacturing	$\Sigma R_A/\Sigma N_{RP}$	R_A = value of resource availability for individual products N_{RP} = number of resources used on products	1 1	(Ghomshei and Villecco, 2009)
RU	Resource Use	Total resources used	Manufacturing	$\Sigma E_U + \Sigma V_{WU} + \Sigma V_{MU}$	E_U = energy used V_{WU} = volume of water used V_{MU} = volume of materials used	kW h m^3 m^3	(IChemE, 2002; Labuschagne and Brent, 2005; Nam, 2008; UNESCAP, 2009)
SW	Solid Waste	Number (or volume) of solid wastes created	Manufacturing	ΣN_{SW} (or ΣV_{SW})	N_{SW} = number of solid wastes generated V_{SW} = volume of solid wastes generated	1 m^3	(Albino et al., 2002; Atlee and Kirchain, 2006; Kainuma and Tawara, 2006; Martins et al., 2007; Wang and Lin, 2004)
SWRR	Solid Waste Reuse Rate	Number (or volume) fraction of reusing solid waste	Manufacturing	$\Sigma N_{SWR}/\Sigma N_{SW} \times 100$ (or $\Sigma V_{SWR}/\Sigma V_{SW} \times 100$)	N_{SWR} = number of reused solid wastes N_{SW} = number of solid wastes generated V_{SWR} = volume of reused solid wastes V_{SW} = volume of solid wastes generated	1 1 m^3 m^3	(Wang and Lin, 2004)
TD	Travel Distance	Distance traveled by products from production facilities to distribution centers	Transportation	Σd_T	d_T = distance traveled by a product between its production and distribution	km	(Carlson and Rafinejad, 2011)

TE	Transportation Emissions per Unit	Mass of emissions released from transportation per number of units produced	Transportation	$\Sigma m_T/\Sigma N_Q$	m_T = mass of emissions from transportation of products N_Q = number of units produced	kg 1	(Nagurney et al., 2007)
TEInt	Transportation Energy Intensity	Energy input required for transportation per number of units	Transportation	$\Sigma E_T/\Sigma N_Q$	E_T = energy use during transportation N_Q = number of units produced	kW h 1	(NRTEE, 2001)
WC	Waste Chemicals	Number ratio of used chemicals that ends up in production wastes	Manufacturing	$\Sigma N_{ChemW}/\Sigma N_{Chem}$	N_{ChemW} = number of chemicals in waste N_{Chem} = number of chemicals used	1 1	(Sikdar, 2007)
WDI	Water Discharge Intensity	Volume of water discharged per number of units produced	Manufacturing	$\Sigma V_{WD}/\Sigma N_Q$	V_{WD} = volume of water discharged N_Q = number of units produced	m^3 1	(NRTEE, 2001)
WG	Waste Generation	Describes the waste generated by production/transportation process	Manufacturing	Σm_W (or ΣV_W)	m_W = mass of wastes generated V_W = volume of wastes entering the waste stream	kg m^3	(Ijomah et al., 2007; Wang and Lin, 2004; Zhou et al., 2000)
WInt	Water Waste Intensity	Volume of polluted water per units produced	Manufacturing	$\Sigma V_{PW}/\Sigma N_Q$	V_{PW} = volume of polluted water N_Q = number of units produced	m^3 1	(NRTEE, 2001)
WP	Water Pollution	Volume fraction of polluted water in total water discharged	Manufacturing	$\Sigma V_{PW}/\Sigma V_{WD} \times 100$	V_{PW} = volume of polluted water V_{WD} = volume of water discharged	m^3 m^3	(Nam, 2008)
WQ	Water Quality	Physical, chemical and biological characteristics of water	Manufacturing	ΣL_{WQ}	L_{WQ} = level of water quality evaluated	1	(Nam, 2008)
WU	Water Usage	Volume of water used for withdrawal, consumptive, and non-withdrawal	Manufacturing	ΣV_{WU}	V_{WU} = volume of water used	m^3	(Labuschagne and Brent, 2005; Petrie et al., 2007; Sikdar, 2007; Wang and Lin, 2004)
WUtil	Waste Utilization	Mass fraction of wastes reused in generated	Manufacturing	$\Sigma m_{WR}/\Sigma m_W$	m_{WR} = mass of wastes reused m_W = mass of wastes generated	kg kg	(NRTEE, 2001)

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