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How to Quantify Social Impacts in Strategic Supply Chain Optimization: State of the Art

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Abstract

The development of quantitative social indicators and methods for social impact assessment is not yet on par with their environmental counterparts. This deficit is especially apparent in strategic supply chain optimization. This literature study reviews 91 articles on strategic supply chain optimization to identify the state-of-the-art in this field and to derive a meaningful agenda for future research. First, the review gives an overview on social frameworks, how articles use them to justify the selection of specific social aspects in their studies, and the differences in selected aspects between different kinds of case studies. Second, the social objective functions are compared in detail. This includes social indicators, i.e. how certain aspects are measured, and how they are integrated in optimization models as input parameters. This allows for an analysis of the relations between decision variables (e.g. for facility location or material flows) and attributed social impacts, as well as of the aggregation of social impacts with different units within the same function. Our results show that the number of created jobs is often the only or primary indicator. If more than one indicator is employed in objective functions, a sizable number of studies addresses the problem of aggregation by weighting towards a dimensionless, generic social score. This review sheds light on the need for more sophisticated methods of social impact assessment and social Pareto optimization. It also assists researchers in identifying previously used, feasible parameters in optimization models, in order to contribute to a more comprehensive and more consistently applied set of social indicators.

Keywords

systematic literature review; social sustainability; supply chain optimization; objective functions; social indicators; social standards

1 Introduction

Traditionally, the need for an efficient and well-informed corporate Supply Chain Management (SCM) stems from economic pressure due to the need for economic competitiveness and changing markets following globalization (Ansari and Kant, 2017). The economic perspective on SCM has therefore been subject of extensive research for decades and is a well-developed field in academia (Rubio et al., 2008; Stindt and Sahamie, 2014). Beside this traditional perspective, the environmental pillar of sustainability, often subsumed under the terms of Sustainable or Green Supply Chain Management (SSCM, GSCM; Rajeev et al., 2017), has received a high level of scientific interest, also manifesting in growing interest in the subdiscipline of Closed-Loop Supply Chain Management (CLSCM; Guide and Van Wassenhove, 2009; Nuss et al., 2015). The complexity of ecological metabolism has seen increasing research for decades and brought about the methodology of Life Cycle Assessment (LCA). It leaves environmental modelers and practitioners only concerned with the identification of inputs and outputs into and out of the system, but eases the characterization of these inputs and outputs towards a standardized set of environmental mechanisms and damage categories in a holistic, quantitative and standardized manner. It can be applied to SSCM problems (Eskandarpour et al., 2015, Messmann et al., 2019), where it enables a quantitative impact assessment of supply chain decisions.

The case of social sustainability is more intricate. This is particularly true for quantitative supply chain optimization, where stocks and flows can be modeled as inputs and outputs environmentally, but less so in the social dimension. Chazara et al. (2017, p. 137) trace back the difficulties with social assessment to i.a. a lack of theoretical underpinning, the complexity of social indicators, their subjective and qualitative nature, and a lack of data. Generally, social assessments can be carried out on a site-specific or on a generic level. Site-specific assessments, using existent frameworks (see section 3.1), can be conducted as part of case studies (e.g. Hannouf and Assefa, 2017) and may include issues such as fair salary or equal opportunities at a specific location. An example for a generic indicator could be a company's contribution to the local development in different countries (Benoît and Mazijn, 2009; Benoît-Norris et al., 2013). On a more strategic and aggregated level of decision-making, a generic perspective is often required. For the generic assessment of raw materials alone, sophisticated approaches exist (Kolotzek et al. 2018; Manchini and Sala, 2018). Due to its complex and diverse nature, however, comparable approaches in generic decision-making along the entire supply chain are still scarce.

In 2008, Seuring and Müller conclude that a deficit exists in terms of the social pillar of sustainability in sustainable supply chain management in general, after merely 20 of 191 revisited articles addressed social issues. Stindt (2017) reviews methods and sustainability indicators in sustainable supply chain decision-making and lists 26 social indicators applied in 14 articles. He concludes that social aspects are still significantly less elaborated compared to the environmental dimension, and often only used nominally. Cambero and Sowlati (2014) and Ghaderi et al. (2016) explore literature on biomass supply chains specifically. The former emphasize the prevalence of job creation as a social indicator and identify four relevant studies in that field, while the latter focus on optimization approaches and name four types of social objective functions used in seven articles. Similarly, Mujkic et al. (2018) identify eleven articles with explicit social objective functions in multi-criteria supply chain optimization models. They select the Sustainability Reporting Guidelines by the Global Reporting Initiative (GRI, see section 3.1) as underlying framework for social assessment and assort a total of 16 identified indicators to GRI and non-GRI categories. Chen et al. (2014), who analyze articles on facility location selection from 1990 to 2011, choose a similar approach. 52 articles with a total of ten GRI-based location factors of social sustainability are reviewed. Eskandarpour et al. (2015) adopt a more OR-centric perspective on facility location as part of supply network design. In their study, they consider sustainability issues, modeling approaches, methodologies and their application. The authors briefly describe 15 articles on network design that include social aspects, and acknowledge the immense challenges in integrating social aspects quantitatively. Up to now and to the best of our knowledge, the largest samples of articles with social aspects in a supply chain context are presented by Bubicz et al. (2019) and by Barbosa-Póvoa et al. (2018). In an extensive meta-analysis, Bubicz et al. (2019) review 621 articles with social sustainability in a general supply chain context. With the focus rather on the qualitative aspects of reviewed articles, they aim at identifying major trends and gaps in the interface between social sustainability on the one hand, and different stages and entities within the realm of supply chain management in general on the other hand. Barbosa-Povóa et al. (2018) focus more on the Operations Research (OR) side of articles than on the social component itself, and review OR articles with economic, environmental or social dimensions (social: 49 of 220 articles). Two of the main objects of study are the decision level and the applied OR method. 44 of these 49 articles (90%) address social aspects on a strategic level (instead of the tactical or operational), and 36 (74%) use optimization techniques (instead of e.g. decision analysis or simulation).

As a result of this overview, two mutually dependent research gaps can be identified. First, a gap exists with regard to meta-analyses of relevant articles in this field. The social dimension is often only a side aspect compared to economic and environmental ones, and the samples of revisited articles thus often remain relatively small in most reviews. Furthermore, none of the aforementioned studies addresses the quantitative side of integrating social indicators in mathematical models, despite the fact that this is the most intricate part within the interface of socially sustainable supply chain management. This is also the part where the gap to the economic and environmental dimensions is the largest, which leads to the second gap: All of the cited literature reviews agree that the field of quantitative supply chain modeling is highly underdeveloped with respect to the integration of social aspects, and that it lacks a standardized methodology comparable to environmental LCA. Therefore, it is vital to devote more research to the quantification of social aspects (Chen et al., 2014; Osmani and Zhang, 2017), to the selection of meaningful social indicators (Cambero and Sowlati, 2014; Mota et al., 2015b; Rahimi and Ghezavati, 2018; Varsei and Polyakovskiy, 2017), as well as to appropriate modeling approaches (Barbosa-Póvoa et al., 2018; Feitó-Cespón et al., 2017; Pishvaee et al., 2012).

To address both of the aforementioned gaps, the analysis in the article at hand takes an in-detail view on how social aspects and actual social indicators for these aspects are integrated in quantitative, mathematical models. This encompasses the structure and composition of every social objective function and constraints, the relationship between decision variables and social indicators, as well as the units of the objective functions and their constituting terms. This analysis is done consistently from the perspective of quantitative social assessment. The study at hand thus examines the justification behind the selection of social aspects, references to preexisting social assessment frameworks, and how the kind and number of considered aspects depends on the cited frameworks and the focal industry. For the purpose of comparability, and to eliminate additional potential layers of examination, we focus on the strategic decision level and on optimization models as the most prominent OR method. In detail, the following research questions are to be answered:

- What is the state of the art of integrating social aspects in the field of strategic supply chain optimization?
  - **RQ1.** What frameworks for social assessment are referred to, what social aspects are considered, and how is their selection justified?
  - **RQ2.** How are social indicators incorporated into quantitative models?

The remainder of this study is structured as follows: Section 2 outlines the applied method for literature collection and evaluation, as well as giving a meta-analysis of the identified sample. Section 3 presents the results of the literature analysis with a particular attention to the research questions. As its key element, it describes the integration of social indicators into optimization models explicitly. Section 4 covers the issues of aggregating multiple aspects and indicators, and discusses the results. Section 5 concludes the present study with the identification of an agenda for future research.

2 Method

The research methodology is conducted in a systematic manner to guarantee the comprehensibility of the literature acquisition approach, the unambiguity of its scope, the tangibility of the results, as well as the consistency with previous work. For this purpose, a four-step methodology is used, which comprises material collection, a descriptive analysis, category selection, and material evaluation. It was similarly applied by i.a. Seuring and Müller (2008), Ghaderi et al. (2016), Barbosa-Póvoa et al. (2018), and Bubicz et al. (2019) for comparable studies cited in section 1.

2.1 Step 1: Material collection

The material collection is carried out in a careful database research, for which the databases ScienceDirect (SD), Web of Science (WS), and EBSCOhost (EH) are selected. SD is also selected by i.a. Mujkic et al. (2018), SD and EH by Stindt (2017), and SD and WS by Barbosa-Póvoa et al. (2018); each time with the argument that the selected databases cover a vast majority of relevant journals in this field. The used Boolean search string accounts for the interdisciplinarity between the research fields of social assessment and OR-based supply chain management. The latter is considered with an emphasis on the strategic planning level and includes reverse supply chains. The social component of the search string includes social concepts, the acronym of which is nowadays understood without the word “social” per se (corporate social responsibility, CSR, social life cycle assessment, SLCA, see section 3.1). The search was finished on 22 May 2019, and employed the following search string:

(social OR societal OR csr OR slca OR s-lca) AND (“network design” OR “network planning” OR “logistics network” OR “strategic supply chain” OR “supply chain network” OR ”facility location” OR “closed-loop supply chain” OR clsc)*

In order to be referenced in this study, an article needs to meet the following criteria:

- The article is written in English.
- The article includes a problem within strategic supply chain or supply network decision-making.
- The article includes at least one social aspect with a quantitative social indicator in an optimization model.

The latter means that also those articles are excluded that only use metrics or quantitative methods (e.g. data envelopment analysis, DEA, analytical hierarchical process, AHP) for the determination of single social parameters, but without an overall decision-making model. For example, Chazara et al. (2017) develop a comprehensive metric for estimating created direct, indirect and induced jobs, and Azadi et al. (2015) use AHP to evaluate the social sustainability of suppliers. Approaches such as those are valuable for parameter calculation in decision-making models, but do not encompass optimization models themselves. Furthermore, facility location models are excluded, if no supply chain context is apparent (e.g. hospitals, disaster relief centers, wind turbines). Lastly, the impacts from e.g. climate change are also excluded. For example, Tseng and Hung (2014) use "social costs" as an indicator to measure the societal impacts from greenhouse gas emissions, which is considered an environmental, not a social aspect in this study. Ultimately, applying the criteria resulted in a sample of 77 articles from the forward search (SD: 23, WS: 20, EH: 6, SD+WS: 10, WS+EH: 1, SD+WS+EH: 17) and another 14 from a backward search. Therefore, the final sample comprises a total of **91 articles** that are analyzed in this study with respect to the research questions. 78 of which contain a total of 85 social objective functions, while 13 contain social constraints only. The 91 referenced studies are listed in Appendix 2.

2.2 Step 2: Descriptive analysis

The earliest four articles were published in 2000, 2009 (2), and 2011. Since then, the number of published articles per year has been increasing, testifying the existing and growing relevance of the topic in academia in general, and in the field of strategic supply chain management specifically. The release of the Guidelines for Social Life Cycle Assessment (Benoît and Mazijn, 2009) and the ISO 26000 standard (ISO, 2010; see section 3.1) as possible gateways could be adduced as explanations for this recent trend. The short time frame also hints at this article's epistemic presumption that the afore used approaches lack homogeneity in terms of scope and used indicators. The identified articles are written by 219 different authors, and are published in 45 different journals, of which 29 appear in the sample only once (see Supplementary material M2b). This could be explained by the novelty of the topic and by the fact that the social dimension is often not the primary focus, but rather "attached" to whatever topic or problem. By far the most of the identified articles were published in the *Journal of Cleaner Production* (18, 20%). This journal alone accounts for more articles than *Computer Aided Chemical Engineering* (7), *Transportation Research Part E: Logistics and Transportation Review* (6) and *Computers & Industrial Engineering* (4) combined. Despite the focus on the strategic decision-making level, a sizable number of articles was published in production or process-oriented journals. Figure 1 depicts the number of articles per year of publication, as well as the most frequent publishing journals, while Table 1 shows the authors with the most contributions in this field.

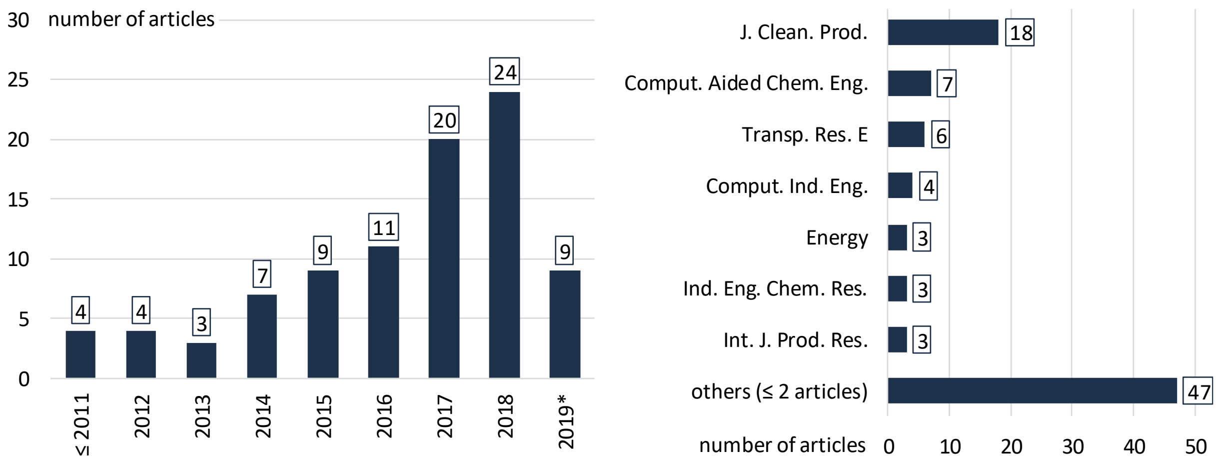


Fig. 1. Number of relevant articles per year of publication and publishing journal (* as of 22 May 2019, incl. articles in press)

Table 1. Contributing authors

Author	Articles	Country of institution
Barbosa-Póvoa, A.P.	6	Portugal
Gomes, M.I.	6	Portugal
Mota, B.	6	Portugal
Pishvaee, M.S.	6	Iran
Carvalho, A.	4	Portugal
El-Halwagi, M.M.	4	USA / Saudi Arabia
González-Campos, J.B.	4	Mexico
Govindan, K.	4	Denmark
Ponce-Ortega, J.M.	4	Mexico
Fathollahi-Fard, A.M.	3	Iran
Hajiaghaei-Keshteli, M.	3	Iran
Mayorga, R.V.	3	Canada
Pourjavad, E.	3	Canada
Razmi, J.	3	Iran
Serna-González, M.	3	Mexico
Tavakkoli-Moghaddam, R.	3	Iran (3) / France (1)
204 others (≤ 2 articles)		

2.3 Step 3: Category selection

The remainder of this article comprises the synthesis of the findings according to preselected categories, and the evaluation of the material with regard to the research questions. The key categories, necessary to answer the research questions, are cited frameworks for social assessment, considered social aspects, and most importantly social objective functions and constraints with their main constituents decision variables and social indicators. Beside these key categories, data on the following additional categories is gathered: the type of case study (focal industry sector and/or product), the direction (forward, reverse) of the modeled supply chain, modeling features, methods for multi-criteria optimization, and included end-of-life-options in reverse supply chains. The entire dataset with all categories and results is given in the Supplementary material M2a. Lastly, step 4, the material evaluation, is carried out in the following section 3.

Beside the social dimension, all of the 91 articles also cover at least the economic dimension, and 78 articles include both an economic and an environmental objective function. The same cannot be said vice versa, i.e. articles with an economic or environmental focus often do not include social aspects (cf. section 1). As is it not the focus of this study, and to keep this section as concise as possible, we refrain from additionally explaining the economic or environmental indicators and objective functions used in the respective articles. For developments in environmental modeling in SSCM, we refer the reader to the comprehensive reviews by Eskandarpour et al. (2015) and Barbosa-Póvoa et al. (2018).

3 Material evaluation

To create a common basis for social assessment and the reasoning behind the selection of aspects in literature, existing independent frameworks for social assessment are introduced, and it is explored which study explicitly references which frameworks (section 3.1). This is followed by a comprehensive overview on considered social aspects (section 3.2), and by an overview on industry sectors of conducted case studies (section 3.3). With frameworks and trends identified, a detailed analysis on the integration of aspects and their indicators into quantitative models is the centerpiece of this study (section 3.4). After a brief exploration of employed modeling approaches and multi-criteria optimization, the sample of articles is divided into two categories. First, there are those articles that optimize social objective functions (section 3.4.1), and second, there are those articles that introduce social constraints to e.g. economic or environmental objective functions (section 3.4.2). For objective functions and constraints, the main epistemic object is the quantitative connection between decision variables and social parameters (section 3.4.3).

3.1 Frameworks of social assessment

Only in recent years, research on the social perspective has begun to catch up. The release of social standards and frameworks has outlined the spectrum of social aspects in different categories. However, due to a lack of homogeneity in social assessment, comparable to environmental LCA, most of the referenced articles choose their set of relevant aspects and respective indicators individually. Here, the existing frameworks of social assessment constitute the nethermost level of commonality and comparability. Even though their current versions are far from being on par with environmental LCA, they are cited in referenced articles as providers of the available array of social aspects, and to justify the selection of the latter for use in the articles' models. However, with only 24 articles, the number of articles that cite a framework is rather small, while 67 do not cite any framework at all. The frameworks mentioned in this section as well as their nomenclature and the aspects and indicators covered by them are detailed in the Supplementary material (M3).

In the field of strategic supply chain decision-making, Social Life Cycle Assessment (SLCA) is cited for its kinship to LCA (including the typical four-step methodology, and in particular their product-perspective), and its subsequent theoretical suitability for supply chain problems ([59] Pishvaee et al., 2014). In 2009, UNEP/SETAC provided the **Guidelines for Social Life Cycle Assessment of Products (GSLCAP)**, distinguishing between five stakeholder categories *workers*, *consumers*, *local community*, *society*, and *value chain actors* (Benoît and Mazijn, 2009). They are further divided into a total of 31 subcategories. The Guidelines were later complemented by the Methodological Sheets for Social LCA, which propose definite units of measurement and data sources for the aforementioned subcategories (Benoît-Norris et al., 2011, 2013). This can be seen as first attempts towards an analogy to the quantitative life cycle inventory and impact assessment of environmental LCA. As for the product-perspective, the Methodological Sheets are also the only framework to differentiate between a site-specific (e.g. the social performance of a specific company or site) and a generic (e.g. country-specific, industry-specific, product-specific) assessment. For example, a site-specific indicator for the subcategory *health and safety* in the stakeholder category *workers* could be the number of injuries in a specific plant of the company, while the generic variant of the indicator could be the occupational accident rate by country (Benoît-Norris et al., 2013, p. 118). The latter facilitates decision-making problems with a more aggregated scope and multifarious decisions, while the former suits evaluations or comparison studies between existing sites or companies, or decision problems with a limited number of discrete possible decisions. For the generic indicators, quantitative or semi-quantitative data sources are proposed for almost all of the existing aspects, such as international databases. Furthermore, the Product Social Impact Life Cycle Assessment database (PSILCA) is directly based on the categorization of the GSLCAP and offers data for 50 indicators in 15,000 sectors and 189 countries (Ciroth and Eisfeldt, 2016). Within the 91 referenced articles, the GSLCAP are only cited 6 times (7%, Table 2).

The Sustainability Reporting Guidelines are a framework developed by the **Global Reporting Initiative (GRI)** between 2000 and 2013 in versions from GRI G1 to G4 (GRI, 2013), and cover economic, environmental, and social aspects. They were succeeded by the GRI Sustainability Reporting Standards (GRI, 2016). These frameworks aim at supporting organizations alongside the supply chain in evaluating their performance in all three pillars of sustainability. In contrast to SLCA, the frameworks' perspective is on companies and other organizations. GRI defines the social pillar of sustainability as the social consequences of an organization on social systems (GRI, 2013). In the social category, G4 (like G3.1) distinguishes between the four subcategories *labour practices and decent work, human rights, society, and product responsibility* that are further subdivided into 30 aspects, and proposes 48 indicator measurements or questions with the aid of which the aspects can be measured. The newer and modular GRI Standards consist of 19 social standards with 40 indicators in total. However, unlike the G4, which are cited in 5 articles (G3.1: 4 articles), the GRI Standards are not mentioned in any of the articles.

Likewise, the **International Guidance Standard on Social Responsibility, ISO 26000,** by the International Standardization Organization is organization-oriented. It distinguishes between seven categories, called core subjects (ISO, 2010). They comprise *organizational governance*, *human rights*, *labor practices*, *environment*, *fair operating practices*, *consumer issues*, and *community involvement and development*, which are subdivided into 36 issues. The ISO 26000 are the most frequently cited framework, with citations in 17 of 91 articles (19%). In addition to the ISO 26000, a small number of studies cites other international standards, i.e. **SA8000** by Social Accountability International (SAI, 1997) and AA1000 by the Institute of Social and Ethical AccountAbility (AccountAbility, 1999).

Other frameworks include the afore cited AA1000, Logistics Social Responsibility (LSR, Carter and Jennings, 2002), the Ethical Trading Initiative's Base Code (ETI, 2018), the Fair Labor Association's Code of Conduct (FLA, 2011), and the United Nations Global Compact (UNGC, 2007).

Partially created by the same authors as the GSLCAP, the Social Hotspots Database (Benoît-Norris and Norris, 2015; SHDB, 2019) is a product-focus database, which allows for input/output modeling of products and provides data for numerous regions and industry sectors. It also offers metrics for characterization and social impact assessment in five categories (health & safety, community, governance, human rights, labor rights). Despite this being a notable step in the development of a quantifiable social dimension, it is neither used nor cited by the referenced studies. Other possible non-cited approaches or frameworks comprise, inter alia, the United Nations Sustainable Development Goals (UN, 2015) or the EU Cohesion Report (European Commission, 2017). The latter is released triennially and evaluates the current state and progress of the socio-economic cohesion of the union on the basis of a plethora of indicators, which could be appropriated for an assessment of social sustainability in accordance with the political interests and development goals of the EU. The report is not cited in the referenced articles explicitly, however, single indicators from it have been adopted with reference to the EU's development strategy, e.g. population density by [49] Mota et al. (2015c). Lastly, single industry-specific approaches have been developed for sectors that require additional qualified perspectives on sustainability, such as for agricultural produces (Meul et al., 2008), also without citation in the referenced sample.

Among all of the articles, those that cite no framework at all and either device the social dimension individually or base their selection on an unstructured source comprise the largest group. Those articles that do cite a framework do so in one of three ways, as presented in Table 2. A small number of articles bases their selection of social aspects *specifically* on the frameworks' content, i.e. by citing specific categories and considering aspects accordingly. Others cite the respective framework *generally* as a foundation of the article's social assessment, and the last group mention a framework, but *unrelated* to the article's own methodology, e.g. as part of the literature section (in Appendix 2 and Supplementary material M2a, these three differentiations are represented in bold, plain, and italic letters respectively).

Table 2. Number of articles that cite frameworks and their categories

Framework	Cited specifically	Cited generally	Cited, but unrelated	TOTAL
GSLCAP	4		2	**6**
Workers	3			
Consumers	2			
Value Chain Actors	1			
Local Community	4			
Society	3			
GRI G3.1	1		3	**4**
GRI G4	2		3	**5**
Labor practices & decent work	3			
Human rights				
Society	2			
Product responsibility	1			
ISO 26000	7	5	5	**17**
Organizational governance	1			
Human rights	2			
Labor practices	6			
Environment	2			
Fair operating practices	2			
Consumer issues	2			
Community involvement & development	5			
SA8000		3	5	**8**
Other framework(s)		2	5	**7**
No framework cited				**67**

3.2 Social aspects

For the purpose of clarity and comprehensibility in this section, we group the aspects of different frameworks that were cited in different articles, but which are substantially comparable. For example, the GSLCAP's subcategory "local employment" and GRI's aspect "employment" are summarized under "job creation" in this section. This allocation is documented in the Supplementary material (M3a), together with an overview on all aspects covered by the mentioned frameworks. The categorization is comparable to the one applied by Bubicz et al. (2019). They base their aspects on the categories by GRI, i.e. labor practices and decent work, human rights, society, and product responsibility. Since it plays only an insignificant role in the articles in the study at hand, the aspect of "human rights" is subsumed under "other aspects". The remaining ones can be matched to "our" aspects creation of jobs, work safety, employment quality, economic development, living conditions, customer safety, and customer satisfaction.

With 63 of 91 articles (69%), the **creation of jobs** due to strategic decisions is by far the most prominent of the considered social aspects. In most cases, this means the summation of the sheer number jobs created due to decisions. Only a small number of articles distinguishes between directly and indirectly created, as well as induced jobs. Direct jobs are those jobs "that the [supply chain] activity has created directly" (Chazara et al., 2017, p. 137), e.g. by opening a new facility with a certain number of employees. Indirect jobs are created at other supply chain stakeholders, e.g. suppliers or subcontractors, as a result of the activity (ibid.), and induced jobs represent the impact that direct or indirect jobs have on employment in the local economy (ibid.). This differentiation is only taken into account by [42, 43] Miret et al. (2016, 2015), [85] You et al. (2012), and [86] Yue et al. (2014).

Work safety is another frequently considered employment-related aspect, which foremost comprises the health and security of employees. It is mostly quantified as lost working time due to injuries (e.g. [25] Fathollahi-Fard et al., 2018; [59] Pishvaee et al., 2014), subject to decisions on technologies, or product or material choices.

Other work-related aspects, subsumed under the term **employment quality**, include inter alia the happiness of employees (e.g. [03] Allaoui et al., 2018), the fair distribution of (an invariant amount of) created jobs ([04] Anvari and Turkay, 2017), qualification and availability of workforce (e.g. [15] Costa et al., 2017), training and skill development (e.g. [35] Jakhar, 2015), or discrimination ([18] Das and Shaw, 2017).

Two major aspects concern the relation to the region that is affected by respective supply chain decisions. The **economic development** of a region often refers to the prioritization of those regions with a lesser degree of development, which could be measured by means of the Human Development Index (HDI, e.g. [08] Babazadeh et al., 2017), the gross domestic product (GDP, e.g. [50] Mota et al., 2018), population density (e.g. [49] Mota et al., 2015c), or unemployment rates (e.g. [46] Mota et al., 2013). Similarly region-oriented, the aspect of **living conditions** comprises medical & education access (e.g. [04] Anvari and Turkay, 2017), crime control, road infrastructure availability, political stability ([15] Costa et al., 2017), discrimination, abuse of human rights ([18] Das and Shaw, 2017), and visual pollution ([33] Habibi et al., 2017).

Customer-related issues are the least frequently considered aspect. Namely, **customer safety** often depends on the choice of technology (e.g. [58] Pishvaee et al., 2012; [91] Zhu and Hu, 2017), and is considered in eight studies. **Customer satisfaction** is part of social optimization in ten studies (e.g [28] Feitó-Cespón et al., 2017; [78] Soleimani et al., 2017). However, as customer satisfaction could naturally be interpreted as an economic motivation, it is part of a vast array of models outside of the referenced sample, e.g. as a demand satisfaction constraint, but without being listed explicitly as a social objective. The specific integration of all of the aforementioned aspects and their respective indicators in quantitative optimization models is the focus of section 3.4.

As observed earlier, only a rather small number of articles cites any framework at all (Figure 2, left). However, it can be stated that articles that do not cite any framework consider on average 1.6 aspects (67 articles consider a total of 108 aspects), whereas the other 24 articles consider on average 2.5 aspects (60/24). Among them, the number is even higher (2.7, 35/13) for those 13 articles that cite frameworks explicitly to justify the selection of aspects. With reference to sections 3.4 and 4, it bears mentioning that the number of considered social aspects in a study does not allow for a judgement about the complexity or sophistication of its objective function. Quite the contrary, if several aspects are weighted (e.g. by AHP) towards a single social "score", which is then used as a single model parameter, the results are often less tangible than with fewer indicators with actual units.

In addition to the *number*, the *kind* of aspects also differs between articles that do and articles that do not cite a framework (Figure 2, right). In articles that do not, the share of employment quality, living conditions, customer satisfaction and other aspects is higher than in those that do. For customer satisfaction, an aspect that crosses the border to the economic dimension, this is because the aspect is not part of any framework. Employment quality, living conditions and other aspects are more diverse in the used indicators (cf. Supplementary material M1), as existing frameworks offer more readily usable indicators for e.g. job creation, work safety, and economic development. Those articles that cite frameworks, but not specifically, mostly only consider job creation and economic development (and work safety and customer safety to a lesser degree). When frameworks are cited specifically for the selection of particular aspects, the array of considered aspects is more diverse.

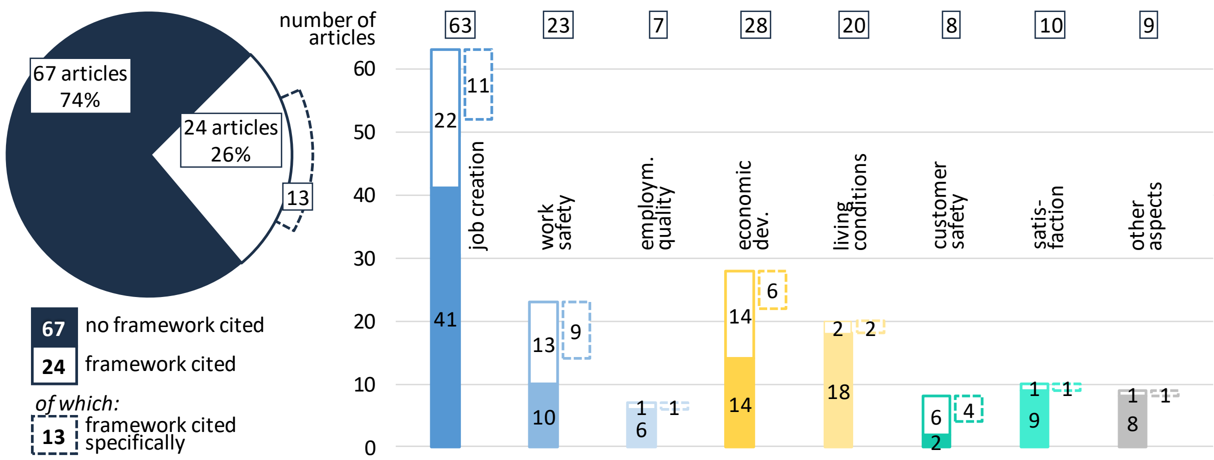


Fig. 2. Share of studies that cite or do not cite a social framework (left), number studies with different social aspects, and distribution of aspects depending on the type of framework citation (right)

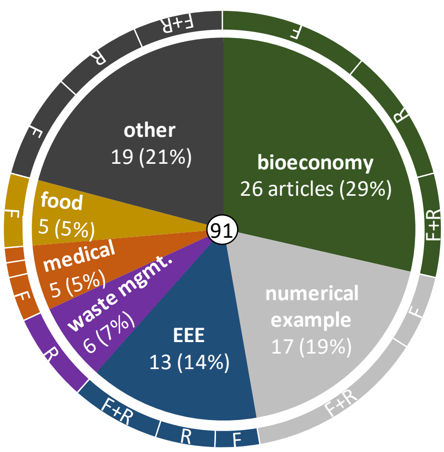
3.3 Types of case studies

The industries and/or products that are focal in the case studies conducted in the referenced articles are categorized into seven groups, as presented in Figure 3. In addition, Figure 3 provides information of the type of supply chain (F = forward, R = reverse, F+R = both forward and reverse elements), as well as the considered social aspects per group.

It is noticeable that articles that optimize a supply chain in the field of **bioeconomy**, i.e. biomass to energy or biomass to fuel, comprise the largest group with 26 articles (29%). This is testament to the great relevance that bioeconomy has gained in recent years (Bugge et al., 2016). They are often based on an inherent sustainable motivation (e.g. [08] Babazadeh et al., 2017; EuropaBio & ESAB, 2006, p. 9), which could explain the fact that optimization studies on bioeconomy are most likely to be subject to all three pillars of sustainability instead of just one or two. Different from what might be expected, this is not mainly due to the inherent conflict between e.g. food and fuel for first-generation biofuels, or for arable soil between food crops and energy crops such as switchgrass. Of the 26 articles, only four ([16], [42], [52], [30]) deal with this issue explicitly in their models (here: subsumed under the aspect of living conditions). In contrast, it is noticeable that the 26 articles on bioeconomy only include a total of 32 social aspects (on average 1.2 aspects per article). Not only is the social aspect of job creation the most important one in bioeconomy with 18 articles, but also is bioeconomy the group in which job creation has highest importance relatively. The differentiation between forward and reverse supply chains for bioeconomy articles differs from those in the other groups. On the one hand, one could argue that biomass (food crops, energy crops, and agricultural residues) is raw material in forward supply chains that produce electricity or fuels. On the other hand, the well-known report by the Ellen MacArthur Foundation (2013, p. 24) promotes the concept of cascade use of feedstock as an important part in a development towards a circular economy. To account for this fact and to enable the differentiation between forward and reverse supply chains in bioeconomy articles in this study, we consider the use of crops (both food crops and energy crops) to be "forward", while biomass from agricultural residues is classified as "reverse".

The 17 articles (19%) without an explicit real-world case study, where e.g. the focus is on presenting a supply chain model, social indicators, or a solution algorithm with a **numerical example** only, consider 29 aspects (1.7 aspects per article). This is also the group with the highest share of articles that consider work safety, which could be explained by the fact that a widely accepted indicator exists (lost days due to work damages, see sections 3.4 and 4), while at the same time a numerical example without a real-world background avoids the issue of data availability. Articles on electric and electronic equipment (**EEE**) comprise the third largest group with 13 articles (14%). Despite the small number, they include the most social aspects (36; 2.8 aspects per article), and also the highest number of articles where economic development is a considered aspect. With ten of the 13, a large share of articles model a reverse supply chain or one with reverse elements (e.g. CLSC), which can be traced back to the high prominence of especially waste EEE (WEEE) in the fields of reverse logistics and circular economy in general (Islam and Huda, 2018).

Groups with much smaller numbers are **waste management** (6 articles, 7%), the **medical industry**, and the **food industry** (5 articles each, 5%). For waste management, living conditions are the most important social aspect, which is mostly affected by the distance of waste facilities to urban areas and the obnoxious effects caused by them. In addition, waste management is the only group in which job creation is only an insignificant aspect. For the groups of medical industry and food industry, the high share of forward supply chains is apparent. The 19 articles (21%) with **other** industries or products (≤ 3 each) include inter alia car tires, construction and demolition (C&D), and steel production.



		job creation	work safety	employm. quality	econ. dev.	living conditions	customer safety	satisfaction	other aspects	
		63	**23**	**7**	**28**	**20**	**8**	**10**	**9**	**Σ aspects**
bioeconomy	**26**	18		1	4	7		1	1	32 (1.2 per art.)
numerical example	**17**	12	7	1	2	1	1	4	1	29 (1.7 per art.)
EEE	**13**	10	5	3	10	2	2	2	2	36 (2.8 per art.)
waste management	**6**	1	1		1	5	1	1	2	12 (2.0 per art.)
medical industry	**5**	5	3		2		2			12 (2.4 per art.)
food industry	**5**	5	1	1	3	1			1	12 (2.4 per art.)
other industry	**19**	12	6	1	6	4	2	2	2	35 (1.8 per art.)

Fig. 3. Share of industry sectors (left) and number of considered social aspects per industry sector (right)

Overall, 33 articles deal with a purely forward supply chain, 26 articles with a reverse supply chain, and in 32 articles, the supply chain has both forward and reverse elements. Of the combined 58 articles with partially or solely reverse elements, those end-of-life options with a lower priority according to the European waste hierarchy (Directive 2008/98/EC) prevail in numbers over those with a higher priority. Recycling, incineration, and disposal appear in 34, 9, and 23 articles respectively (38 different articles in total). Remanufacturing, refurbishment, and preparation for reuse (cleaning, repair, and/or direct reuse) appear less frequently with 14, 4, and 11 times respectively (20 different articles in total), yet especially refurbishment and preparation for reuse are associated with environmental and social (affordable products, local employment creation) benefits alike (Devoldere et al., 2009; O'Connell et al., 2013). For details on end-of-life options, see Supplementary material M2a.

3.4 Social modeling

Social objective functions and constraints, independent of the underlying modeling approach, are defined by their decision variables and parameters. Social parameters as model input need to be quantitative, or at least quantifiable for use in model constraints. This circumstance renders socially sustainable decision-making much more intricate than merely qualitative case studies, and it renders decision-making in the social dimension more intricate than in the economic or environmental one. Appendix 2 and Appendix 3 present employed modeling features. Social objectives, constraints, as well as their variables and parameters are analyzed in the following sub-sections.

As most of the referenced studies cover at least one additional dimension (other than the social), multi-criteria decision-making, i.e. finding trade-offs between the social dimension and the economic or environmental ones, is an issue. Figure 4 shows that the vast majority of studies applies advanced methods to find efficient solutions between economic/environmental and social objectives. This is in contrast to how studies deal with different goals *within* the social dimension (this is discussed in section 4.2). 37 studies use the ε-constraint method (twelve of which use AUGMECON, augmented ε-constraint), and 26 apply metaheuristics to calculate Pareto frontiers between the goals. Within metaheuristics, generic algorithms (GA; and the non-dominated genetic algorithm II, NSGA-II) dominate. Only a minority does not apply multi-criteria methods (ten articles, i.e. only optimizing different objective functions separately), or applies methods such as weighted sums to aggregate different goals towards a dimensionless score.

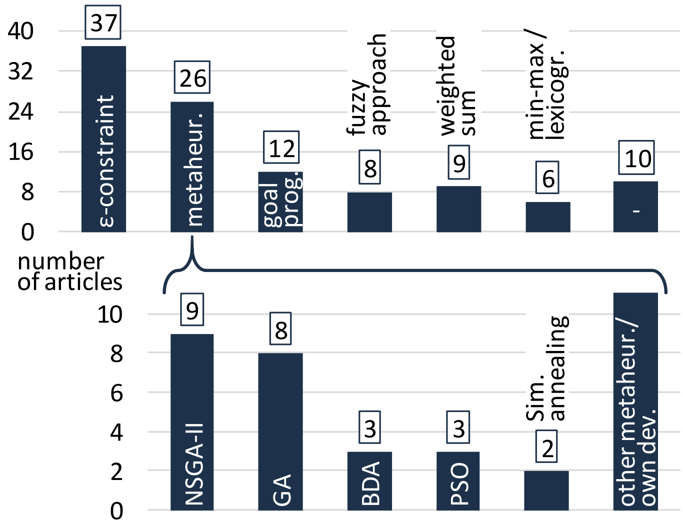


Fig. 4. Number of articles with techniques for multi-criteria optimization

3.4.1 Social objective functions

The design of the objective function is the decisive factor in how social aspects are considered quantitatively. This includes the choice of decision variables that have a social impact (independent of the variables used in economic or environmental functions), and the social indicator, i.e. how the social impact of decisions is measured. Appendix 5 and Supplementary material M4a summarize the social objective functions used in the referenced articles in a, for the sake of comparability, codified and simplified form. The second column indicates whether the function aims to maximize or minimize. In the fourth column, the social indicator is given, which expresses the social impacts of the decision variables in the same line (in columns further to the right). The nomenclature is given in Appendix 4 and in the Supplementary material M1. Each combination of indicator and decision variable within the same line is a term (or group of identical terms) in the function. For example, the function by [38] Kafa et al. (2015) reads as "Maximize the number of jobs created due to facility location decisions + the number of jobs due to decisions on supplier selection". Decision variables in square brackets indicate that this decision is part of the indices of another variable. For example, [23] Eskandari-Khanghahi et al. (2018) maximize the number of jobs created due to decisions on facility locations with a certain facility capacity.

The third column lists aggregators used to combine terms of different lines. If the unit is the same in different lines or if both can be converted into each other (e.g. [32] Govindan et al., 2016b), the aggregator may just be an arithmetic operator; but if indicators of different units are employed, a sizable number of studies aggregates them by weighting. For example, [81] Tsao et al. (2018) maximize the weighted sum of three terms: the number of jobs created due to decisions on facility location with a certain facility technology (i.e. the term unit is "jobs"), the days lost from work damages due to decisions on facility location with a certain technology and a certain product type (i.e. the term unit is "time"), and the fraction of potentially hazardous products dependent on the amount produced of a certain product type and with a certain facility technology (i.e. the term unit is "potentially hazardous products"). Due to the weighting, the overall unit of the objective function is a social score. Six out of 16 studies determine the weights by AHP, while in four studies, the weights follow the judgment of an expert or decision-maker. [80] Tsao and Thanh (2019) test different values, and [36] Jiang et al. (2018) apply equal weights. In another four studies, the origin of the weights are not stated.

The table in Appendix 5 is sorted primarily by the unit of the objective function, and secondarily by the unit of terms (and then lexicographically). The units are given explicitly in the Supplementary material M4a. The list begins with functions that solely maximize jobs (directly or indirectly created, or induced), followed by jobs that are weighted by another indicator. For example, [49] Mota et al. (2015c) maximize the number of jobs created due to decisions on facility locations and inversely weighted with the regional population density, so that jobs in less populated regions are favored. Therefore, the unit is “jobs (eq)” (“job equivalents”), since the term does represent job opportunities created, but by weighting with the population density to favor regions a lower density, the term’s value does not necessarily represent an actual number of jobs. The next set of function encompasses those with the unit “time”, followed by one function where costs are weighted by distances and jobs ([67] Ramos et al., 2018). Those functions in which the unit is a social “score” comprise the largest group. They can be divided in those functions where the indicator itself is already a dimensionless score, usually determined by multi-criteria decision-making (MCDM) methods, such as AHP, and those that employ a vast array of different indicators, but weight the terms in a utility function, as described in the paragraph above. The list is concluded by objective functions with the units “distance”, “facilities”, “facilities (eq)”, “amount”, and “amount (eq)”. For example, [24] Farrokhi-Asl et al. (2016) maximize the distances between urban areas and the locations of disposal facilities. [47] Mota et al. (2014) maximize the number of facilities, weighted by the inverse of the regional GDP in the first functions, and by the regional unemployment rate in the second function. [28] Feitó-Cespón et al. (2017) optimize the customer service level by maximizing the amount of products shipped to customers, which crosses the threshold to the economic dimension, although it is called a “social goal” in the study.

3.4.2 Social constraints

The social constraints can be sorted into two groups (Appendix 6, Supplementary material M4b). The first group are those constraints that directly restrict the primary economic or environmental functions. These constraints are very similar to social objective functions, modeling-wise and in the choice of variables and social parameters. For example, the profit maximization function by [54] Özceylan et al. (2017) is restricted by a lower limit for jobs created, and by an upper limit for days lost due to work damages (both due to facility location decisions with respective facility technology). The formulation is comparable to e.g. the objective function of [32] Govindan et al. (2016b) or the two objective functions by [25] Fathollahi-Fard et al. (2018). The nine articles of this groups are included in further analyses in section 3.4.3.

The other group are those studies that follow a two-step approach, where, with one exception, the programming model of the second step is fed with favorable solutions pre-selected in the first step. [08] Babazadeh et al. (2017) pre-select possible facility locations by criteria such as the human development index (HDI), population, and climate, before solving a MILP model that minimizes costs of a biodiesel supply chain. Similarly, [12] Bouzembrak et al. (2013) use a GIS model to consider an array of economic, environmental, and social aspects, using expert questionnaires. Identified possible locations for sediment treatment facilities are then subject to cost minimization in a MILP model. Social aspects include possible detriments to living conditions, such as nuisances from facilities, pollution, security, and effects on health. [19] Dehghani et al. (2018) identify feasible locations for photovoltaic production facilities by data envelopment analysis (DEA), considering technical, geographic and social (population density) criteria. The entire supply chain is then optimized following the goal of cost minimization. Vice versa compared to the aforementioned articles, [15] Costa et al. (2017) use a macro-location MILP model to optimize a combined economic-environmental objective function, the results of which are the solution space for a micro-location model, which is fed with aspects such as crime control or political stability. The micro-location model is realized by goal programming and not comparable to the objective functions in section 3.4.1. As this group of four articles is hardly comparable to the first group in terms of the modeling approach, these articles are not included in further analyses in section 3.4.3.

3.4.3 Relation between social parameters and strategic decisions

Decisions in social objective functions and constraints have been attributed with different social effects in literature. It is apparent that in models for social optimization in particular, the selection of indicators and decision variables can be mutually dependent, as some variables may facilitate or inhibit certain indicators. For example, decisions on facility locations can simply be attributed with the amount of jobs that are created by them. Lost days due to work damages, however, can only be included, if the model's decisions relate to this indicator in the first place (e.g. decisions on product types or facility technologies). [42] Miret et al. (2016) point out that some decisions are not or only negligibly connected with many social criteria. Table 3 deals with this relationship. Here, decision variables (vertical axis) and social parameters (horizontal axis) are ordered by the number of articles in which they are employed. The matrix between variables and parameters indicates the number of studies in which a variable is quantified by a parameter. For example, the by far most prominent combination is between facility location decisions (*FL*) and jobs created (*job*). In 46 of 68 studies (68%) with a facility location decision, this decision is quantified by the number of jobs created by the decision, and in 46 of 48 studies (96%) that use jobs as a parameter, decisions on facility locations contribute to this indicator. Other frequently employed indicators for facility location (*FL)* decisions are lost days from work damages (*ldd*, 15), generic social scores (*soc*, 14), the regional weights of regional development (*dev*, 10) and unemployment (*ump*, 9), the economic value created (*ecv*, 5), population density (*pop*, 5), or the distance between locations and e.g. urban centers (*dis*, 4). Beside facilities, jobs are usually created by decisions on transport quantities (*QT*, 17), facility technologies (*FT*, 21), production quantities (*QP*, 16), facility capacities (*FC*, 17), and decisions on product types (*PT*, 10). Other noticeable combinations include the parameter of lost days from work damages (*ldd*). In the 17 models in which the parameter is used, decisions on facility locations (*FL*) are responsible (at least partially) in 15 articles (94%), and 13 of 27 articles (48%) that include decisions on facility technologies (*FT*) quantify this decision with lost days. With a few exceptions, the other combinations only appear inconsistently, or do not exist at all. Parameters such as access to education (*edu*), medical access (*med*), or the security level (*sec*) are even used only once, despite the fact that [04] Anvari and Turkay (2017) prove with their article that applicable quantitative indicators can be found for these aspects.

Table 3. Number of articles in which the social effects of decisions (vertical axis) are quantified with different social parameters (horizontal axis) (nomenclature in Appendix 4; numbers from objective functions and constraints)

		job	*ldd*	*soc*	*dev*	*ump*	*ecv*	*pop*	*dis*	*dem*	*haz*	*nui*	*cost*	*hrs*	*sat*	*edu*	*med*	*sec*	*was*	*(none)*
		48	**17**	**15**	**11**	**9**	**6**	**6**	**6**	**5**	**4**	**3**	**3**	**2**	**2**	**1**	**1**	**1**	**1**	**10**
FL	**68**	46	15	14	10	9	5	5	4			2	2	2		1	1	1		2
QT	**36**	17	7	4	2	1		2	3	4		1	3	1		1	1	1		3
FT	**27**	21	13	1	2	2		1	1		4	1		2					1	
QP	**26**	16	6	1	1		1		1		4		1	2					1	1
FC	**22**	17		5	4	3	3	1												
PT	**18**	10	2	2			1		1		1		2	2	1					1
QR	**12**	7		2					1				1	1						1
SU	**9**	4		3	1	1	1		1				1	1	1					
QU	**9**	6	5	1											1					1
TM	**7**	3		2	1								1		1					
TL	**6**	4			1	1									1					1
HR	**3**																			3
QI	**2**	2																		

4 Discussion

The presented results enable statements about the kind and number of indicators employed as well as on how indicators with different units within one objective function are aggregated.

4.1 Small number of consistently applied indicators

The analysis in section 3.4 and Table 3 allows for two perspectives. First, it gives an overview on the social impacts that different types of decisions are attributed with. This helps to identify gaps in the field of social assessment: Where are additional generically applicable social indicators needed? Second, from a modeler’s perspective, this helps to identify how decisions in existing optimization models could be quantified from a social perspective. This may assist researchers in choosing suitable indicators for the social parameters in their objective functions, based on the state of the art. The analysis of the article at hand may thus contribute to a larger number and a more consistently used set of social indicators in the field of strategic supply chain optimization.

Only few articles attempt to apply a larger number of indicators. [59] Pishvaee et al. (2014) and [91] Zhu and Hu (2017) use similar objective functions and indicators. Both weight the number of jobs created by facility location decisions with unemployment rates and the economic value created with a regional development index, to promote locations with higher unemployment rates and lower development. Furthermore, they consider days lost due to work damages from location and technology decisions, as well as weighting the number of needles and syringes manufactured using a certain technology with the respective average fraction of potentially hazardous products. [04] Anvari and Turkay (2017) take another approach and weight the outgoing flow of produced electronics products with regional unemployment rate and population density (to account for job distribution equity), with a regional development index (to account for development equity), with a security level defined as crimes per person in a region, with a medical access level (calculated with doctors per population figure and hospital beds per bed demand), and with an education access level (using number of teachers, school seats, number of pupils and students). Lastly, while employing only few indicators per se, [05] Arampantzi and Minis (2017) argue that their objective function covers a diverse array of social aspects. Here, local community development, support of less developed countries, employee satisfaction, stable employment, and work safety are each expressed in employee-periods.

Of the 188 indicators proposed in the methodological sheets for the GSLCAP (Benoît-Norris et al., 2013), 67 are quantitative (and another 110 semi-quantitative). Of those 67 indicators, 32 are labeled "generic", as opposed to site-specific ones. They represent 17 (of 31) GSLCAP subcategories, of which nine are in one way or another covered by the reviewed articles (cf. Supplementary material M3a, M3b), although not necessarily by the indicators proposed by UNEP. This leaves eight subcategories with generic, quantitative indicators proposed for in the GSLCAP, which find no representation in the referenced articles. Some of these are ambiguous with regard to strategic supply chain optimization; for instance, whether the presence of feedback mechanisms in a sector or country is a reason in favor of or against a location decision. However, innovative approaches such as in the aforementioned study by [04] Anvari and Turkay (2017) as well as previously unused indicators such as average or minimum wages in a sector or country may, e.g. if put in relation with the anticipated wages of the newly created jobs, affect the social sustainability of such a decision.

Currently, created job opportunities clearly prevail in modeling. This fact may be traced back to two main reasons: First, linking network decisions, such as the opening of a facility (see section 3.4.1), to a tangible number of created jobs requires the least assumptions and thus yields the benefit of simplicity for modelers. Second, it is thoroughly researched and widely acknowledged that unemployment leads to real, quantifiable negative consequences, which justifies the selection of this aspect for many modelers. Breuer (2015) empirically show a statistical relation between unemployment and suicide rates, and Brand (2015) gives an account on the manifold consequences of job losses, which range from financial security to i.a. social isolation, lowered self-esteem, and anxiety. Furthermore, unemployment is linked to property crimes (Aaltonen et al., 2013) as well as health problems (Kroll and Lampert, 2009). However, most studies only add up the sheer number of jobs, and do not differentiate by the kind (direct, indirect, induced, cf. section 3.2) or the value of the job created. Exceptions are the limited number of studies that weight jobs by e.g. population density, regional development indices, or unemployment rates to account for the fact that a new job is more worth in less densely populated or less developed regions, or in those with a higher unemployment rate. [73] Santibanez-Aguilar et al. (2014) acknowledge that a job in different stages of the supply chain may impact society differently and cite the Jobs and Economic Development Impact (JEDI) model as a possibility to account for this fact (NREL, 2012). Lastly, [67] Ramos et al. (2018) include wages paid, so that a created job with a higher wage yields a higher social benefit.

4.2 Simplistic aggregation methods

The aggregation of different indicators within the same objective function is another difficulty, which again goes back to a missing impact assessment with similar sophistication as for environmental LCIA.

There, different environmental mechanisms and their impacts (midpoint level), e.g. global warming potential (in kg CO_2 eq.) and land use (in m^2a crop eq.) may account for a comparable damage on the area of protection of ecosystems, which means that the damage of both impacts can be measured in the same unit (species years; examples for ReCiPe 2016, Huijbregts et al., 2017). In the realm of social impact assessment in general and optimization models in particular, different approaches have been applied, none of which is able to achieve a degree of unanimity comparable to environmental LCIA's endpoints.

Figure 5 depicts how social impacts/effects are aggregated within one objective function across different units. For example, if an objective function contains the term *job* × *FL*, the unit of this term is "jobs" (34 articles). If the term is *job* × *ump* × *FL*, the unit is "jobs (eq)" ("jobs equivalents", see section 3.4.1; eleven articles). If the objective function consists of only one term, or if all of its terms are measured in the same unit, no further aggregation is needed or the terms can simply be added (e.g. 22 articles for "jobs"). This is true for the majority of the sample with 58 articles. In this case, the overall unit of the objective function is also e.g. "jobs". A total of four articles aggregated terms with the units "jobs" and "time" by translating both units into work time. In all of the other cases where the objective function contains terms with different units, however, these terms are usually weighted as part of a utility function (see objective functions, section 3.4.1), with weights determined by e.g. AHP (for the weights' origins, see Supplementary material M2a). In this case, the unit of the objective function is a dimensionless social "score". It could be argued that this leads to a loss of information about the actual social impact and thus to a loss of tangibility. Together with the 14 articles in which the social indicator is a generic "score" in the first place, these objective functions are the most common with 28 articles, or the second-most common, if "jobs" and "jobs (eq)" are counted jointly.

Nine and six articles (12% and 8%) optimize functions with the units "time" and "amount"/"amount (eq)" (e.g. as metrics for achieving a certain customer service level) respectively, and the number of functions with other units is negligible. However, the overwhelming majority of objective functions thus either maximizes "job" and "jobs (eq)" (in 41% of articles), or a social "score" (in 36% of articles). In addition, there are only seven articles with more than one social objective function ([03], [25], [38], [47], [48], [78], and [84]). Five of them do apply methods of multi-criteria optimization to their economic, environmental, and both social functions, but while Pareto efficiency and trade-offs are often analyzed between the three dimensions (cf. Figure 4), trade-offs *within* the social dimension are never explored in detail. This shows again that, despite commendable aggregation approaches such as by [05] Arampantzi and Minis (2017) as mentioned in section 4.1, the social dimension has not yet reached parity with the other two dimensions in the sense of the triple bottom line.

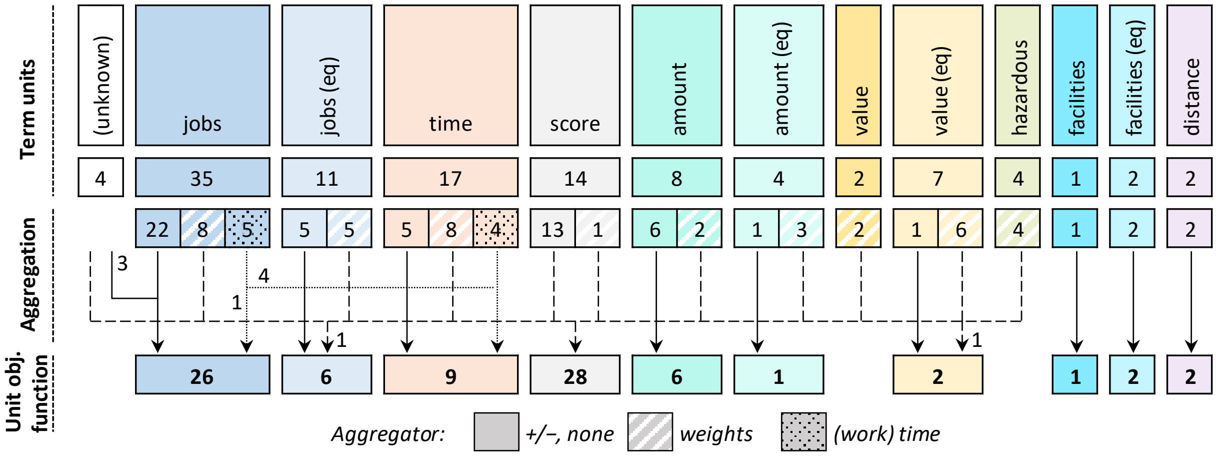


Fig. 5. Number of articles that contain terms (in objective functions) and objective functions with different units, and use different aggregators per term (eq = equivalents, e.g. if weighted by a regional factor)

Two main conclusions can be derived from this analysis: First, as discussed at the outset of this section, a more comprehensive set of social indicators is required. This set then needs to be employed more consistently, following the example of state-of-the-art impact categories in LCA. Not all possible indicators are suited for generic or Greenfield models, and not every parameter is relevant for every problem. However, currently, hardly one article unites all of the applicable indicators in one model. Second, these indicators then need to be aggregated by additional and possibly more sophisticated methods, other than weighting. This could either be accomplished by the development and use of social impact assessment methods (such as the SHDB, which has not been applied in any of the referenced studies) comparable to environmental LCIA, or by applying methods for Pareto and multi-criteria optimization to a larger number of different social objective functions.

5 Conclusion

This study analyzes the state of the art of quantifying social aspects in the field of strategic supply chain optimization – a combination of disciplines, which has received increasing attention in the last years, but which is still in dire need for further development. While the social dimension has been subject of a few meta-studies within that field in the past, the article at hand is the first to explore the application of social indicators on the level of individual objective functions in optimization models. With the results obtained, the research questions can be answered.

RQ1. What frameworks for social assessment are referred to, what social aspects are considered, and how is their selection justified?

Only a quarter of articles cites existing frameworks and standards for social assessment, and of those, only few actually justify the selection of specific aspects this way. Articles that cite frameworks consider over 1.5 times as many aspects as those that do not. The argument could be made that the former also select more generically applicable aspects. The selection of social aspects differs between studies with different focal industries or products, but overall, the creation of job opportunities is by far the most frequently considered aspect, followed by regional economic development and work safety. Customers are the stakeholder category that is considered the least frequently.

RQ2. How are social indicators incorporated into quantitative models?

Currently, the number of jobs created is the only social indicator that is used consistently. However, the fact that the same job can have differing social impacts or benefits in different regions, sectors, or supply chain stages is often neglected. Other somewhat established parameters are the days lost from work damages, generic social scores (e.g. determined by AHP), regional development levels (e.g. measured in GDP per capita), or regional unemployment (in the order of frequency). Social impacts are mostly related to decisions on facility locations. Other frequently used decision variables with social impacts are decisions on transported quantities, facility technologies, manufactured quantities, facility capacities, or product types. Consequently, the most common combination of indicator and variable are jobs created by decisions on facility locations, in 62% of all articles. Many objective functions contain only one indicator, or use weighted scores to aggregate a number of social aspects or units, while more advanced methods are frequently used for multi-criteria optimization between economic or environmental goals. As a consequence, the vast majority of objective functions optimizes “jobs” or social “scores”.

Future research should therefore focus on the set of indicators and on aggregation approaches. In particular, modelers are encouraged to apply a larger set of existing indicators in models more consistently, and to apply Pareto and multi-criteria optimization methods to different social objective functions. The development of a unified approach or framework for social optimization in SCM problems, from a standardized selection process for indicators to ensuring Pareto efficiency between different social goals, could be the next stage in that development. Beyond that, academia in general should take a more interdisciplinary perspective and focus on incorporating the learnings of all relevant disciplines, in order to further advance in the field of social impact assessment.

Appendix

Appendix 1. Abbreviations (shortened, see Supplementary material M1)

Abbreviation	Meaning
AA, AA1000	AccountAbility
AHP, ANP	analytic hierarchy/network process
AUGMECON	augmented ε-constraint
BDA	benders decomposition algorithm
CLSC	closed-loop supply chain
CSL	customer service level
CSR	corporate social responsibility
DEA	data envelopment analysis
DV	decision variable
EEE	electric and electronic equipment
EH	EbscoHost
EPR	extended producer responsibility
ETI	Ethical Trading Initiative
FLA	Fair Labor Association
FSC	forward supply chain
GA	genetic algorithm
GIS	geographic information system
GRI, GRIG3, GRIG4	Global Reporting Initiative (G3.1, G4)
GSCM	green supply chain management
GSLCAP	Guidelines for Social Life Cycle Assessment of Products
ISO, ISO 26000	International Standardization Organization
JEDI	Jobs and Economic Development Impact Model
LCA	(environmental) Life Cycle Assessment
LCIA	Life Cycle Impact Assessment
LSR	Logistics Social Responsibility
MCDM	multi-criteria decision-making
NSGA-II	non-dominated sorting genetic algorithm
OR	Operations Research
PSILCA	Product Social Impact Life Cycle Assessment database
PSO	particle swarm optimization
RSC	reverse supply chain
SA, SA8000	Social Accountability International
SCM	supply chain management
SD	ScienceDirect
SDG	United Nations Sustainable Development Goals
SETAC	Society of Environmental Toxicology and Chemistry
SHDB	Social Hotspots Database
SimAnn	simulated annealing
SLCA, S-LCA	Social Life Cycle Assessment
SSCM	sustainable supply chain management
UNEP	United Nations Environment Programme
UNGC	United Nations Global Compact
WEEE	waste electric and electronic equipment
WS	Web of Science

Appendix 2. Overview on referenced articles (shortened; for full overview see Supplementary material M2a)

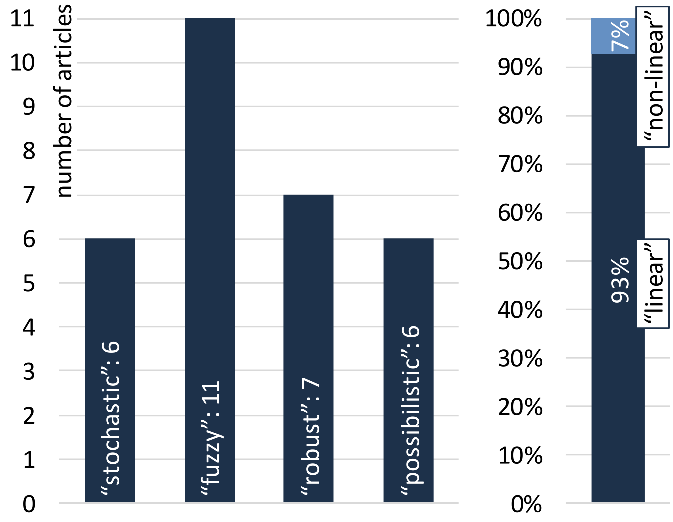
Number	Article	Cited frameworks [1,2]	job creation	work safety	employment quality	econ. development	living conditions	customer safety	satisfaction	other aspects [2]	Industry sector	SC scope [3]	Modeling features [4]	Direction	Objective unit	Term units	Aggregator
[01]	Ahranjani et al., 2018	-	x								bioeconomy	R	RPMILP	↑	jobs	jobs	-
[02]	Alkahtani and Ziout, 2019	-	x								other	R	MILP	↑	jobs	jobs	-
[03]	Allaoui et al., 2018	-	x	x	x		x			*x*	food ind.	F	MILP	↑ ↑	jobs, score	jobs, score	-
[04]	Anvari and Turkay, 2017	**ISO**			x	x	x				EEE	F	MILP	↑	score	amount (eq)	weights
[05]	Arampantzi and Minis, 2017	ISO, *GRIG4*	x	x		x					EEE	F	MILP	↓	jobs	jobs, jobs (eq)	time
[06]	Asefi and Lim, 2017	-					x			*x*	waste mgmt.	R	MIP	↑	score	score	-
[07]	Ayoub et al., 2009	-	x								bioeconomy	R	P	↕	time	time	-
[08]	Babazadeh et al., 2017	-				x					bioeconomy	F	MILP	n.a.			
[09]	Bairamzadeh et al., 2016	ISO, *SA*, *AA*	x								bioeconomy	R	MILP	↑	jobs	jobs	-
[10]	Bal and Satoglu, 2018	**ISO**	x								EEE	R	MILP	n.a.			
[11]	Balaman and Selim, 2016	-							x		bioeconomy	F+R	FMILP	↓	amount	amount	-
[12]	Bouzembrak et al., 2013	-					x				other	R	MILP	n.a.			
[13]	Cambero and Sowlati, 2016	-	x								bioeconomy	R	MILP	↑	time	time	-
[14]	Chen and Andresen, 2014	-		x							other	F	MILP	↓	time	time	-
[15]	Costa et al., 2017	-			x		x			*x*	bioeconomy	F	MILP	n.a.			
[16]	Čuček et al., 2012	-					x				bioeconomy	F+R	MINLP	↓	amount	amount	-
[17]	Darbari et al., 2017	-				x			x		EEE	R	FMILP	↑	score	score	-
[18]	Das and Shaw, 2017	-			x		x		x	*x*	numerical ex.	F	P	n.a.			
[19]	Dehghani et al., 2018	-				x					other	F	RP	n.a.			
[20]	Dehghanian and Mansour, 2009	ISO, LSR	x	x		x		x			other	R	P	↑	score	score	-
[21]	Devika et al., 2014	-	x	x							other	F+R	MILP	↑	score	jobs, time	weights
[22]	Dosal et al., 2013	-				x	x			*x*	other	R	MILP	↑	score	(unknown)	-
[23]	Eskandari-Khanghahi et al., 2018	-	x								medical ind.	F	FPMILP	↑	jobs	jobs	-
[24]	Farrokhi-Asl et al., 2016	-					x				waste mgmt.	R	P	↑	distance	distance	-
[25]	Fathollahi-Fard et al., 2018	**ISO**, SA, *GSLCAP*	x	x							numerical ex.	F+R	SMIP	↑ ↓	jobs, time	jobs, time	-
[26]	Fattahi and Govindan, 2018	-	x			x	x				bioeconomy	R	MILP	n.a.			
[27]	Fattahi et al., in press	-	x			x	x				other	F	SP	n.a.			
[28]	Feitó-Cespón et al., 2017	-							x		waste mgmt.	R	SMINLP	↑	amount	amount	-
[29]	Ghaderi et al., 2018	**GSLCAP**	x			x					bioeconomy	F	RPMILP	↑	score	jobs (eq), value (eq)	weights

[30]	Gonela et al., 2015	-					x				bioeconomy	F+R	SMILP	n.a.			
[31]	Govindan et al., 2016a	-		x	x	x		x	x	*x*	EEE	F+R	MIP	↑	score	score, amount, amount (eq), value	weights
[32]	Govindan et al., 2016b	-	x	x							medical ind.	R	FP	↑	time	jobs, time	time
[33]	Habibi et al., 2017	-					x				waste mgmt.	R	RP	↓	amount (eq)	amount (eq)	-
[34]	Harijani et al., 2017	**GSLCAP**, *GRIG3*, *ISO*, *SA, UNGC*	x	x		x	x	x		*x*	waste mgmt.	R	MILP	n.a.			
[35]	Jakhar, 2015	-	x		x	x	x	x			other	F+R	FLP	↑	score	score	-
[36]	Jiang et al., 2018	-	x			x					food ind.	F	LP	↑	score	jobs, amount (eq)	weights
[37]	Jin et al., 2018	-								*x*	other	R	MILP	↑	score	score	-
[38]	Kafa et al., 2015	-	x	x	x					*x*	EEE	F+R	MILP	↑ ↑	jobs, score	jobs, score	-
[39]	Lin et al., 2019	-	x								bioeconomy	F	FLP	↑	jobs	jobs	-
[40]	Martínez-Guido et al., 2014	-	x								other	F	MILP	↑	jobs	jobs	-
[41]	Martínez-Guido et al., 2016	-	x								bioeconomy	R	P	↑	jobs	(unknown)	-
[42]	Miret et al., 2016	-	x				x				bioeconomy	F	MILP	↑	jobs	jobs	-
[43]	Miret et al., 2015	-	x								bioeconomy	F	MILP	↑	jobs	(unknown)	-
[44]	Mirmohammadi and Sahraeian, 2018	-	x	x							numerical ex.	F+R	MINLP	↑	time	jobs, time	time
[45]	Mota et al., 2015a	*GRIG4*	x			x					food ind.	F	P	↑	jobs (eq)	jobs (eq)	-
[46]	Mota et al., 2013	*GSLCAP*	x			x					EEE	F+R	MILP	↑	jobs (eq)	jobs (eq)	-
[47]	Mota et al., 2014	-				x					numerical ex.	F	MILP	↑ ↑	facilities (eq)	facilities (eq)	-
[48]	Mota et al., 2015b	-	x			x					numerical ex.	F+R	MILP	↓ ↓	jobs (eq)	jobs (eq)	-
[49]	Mota et al., 2015c	**GRIG4**	x			x					EEE	F+R	MILP	↑	jobs (eq)	jobs (eq)	-
[50]	Mota et al., 2018	*GRIG4*, *ISO*	x			x					EEE	F+R	MILP	↑	jobs (eq)	jobs (eq)	-
[51]	Nobari and Kheirkhah, 2018	-	x								numerical ex.	F+R	MILP	↑	jobs	jobs	-
[52]	Orjuela-Castro et al., 2019	-					x				bioeconomy	F	LP	↓	amount	amount	-
[53]	Osmani and Zhang, 2017	-	x								bioeconomy	F+R	SMILP	↑	jobs	jobs	-
[54]	Özceylan et al., 2017	-	x	x							other	F+R	LP	n.a.			
[55]	Pedram et al., 2017	-	x								numerical ex.	F+R	MILP	↑	jobs	jobs	-
[56]	Pérez-Fortes et al., 2012	-	x								bioeconomy	R	MILP	↑	facilities	facilities	-
[57]	Petridis et al., 2018	-				x					bioeconomy	F	MILP	n.a.			
[58]	Pishvaee et al., 2012	**GRIG3**, **ISO**, *SA*, *AA*	x	x				x			medical ind.	F	RPP	↑	score	jobs, time, amount, hazardous	weights
[59]	Pishvaee et al., 2014	**GSLCAP**, *GRIG3*, *SA*, *ETI, FLA, UNGC*	x	x		x		x			medical ind.	F+R	RPP	↑	score	jobs (eq), time, value (eq), hazardous	weights
[60]	Pourjavad and Mayorga, 2018	-	x								numerical ex.	F+R	FMILP	↑	jobs	jobs	-
[61]	Pourjavad and Mayorga, 2019a	-	x								numerical ex.	F+R	FMILP	↓	jobs	jobs	-
[62]	Pourjavad and Mayorga, 2019b	-	x								numerical ex.	F+R	FMILP	↑	jobs	jobs	-
[63]	Rabbani et al., 2018	-	x								bioeconomy	F	MILP	↑	jobs	jobs	-
[64]	Rad and Nahavandi, 2018	-							x		numerical ex.	F+R	MILP	↑	score	score	-
[65]	Rahimi and Ghezavati, 2018	**ISO**	x	x							other	R	SMILP	↑	time	jobs, time	time
[66]	Rahimi et al., 2019	**ISO**	x	x							numerical ex.	F	MINLP	↑	time	jobs, time	time

[67]	Ramos et al., 2018	-	x							food ind.	F	MIP	↑	value (eq)	value (eq)	-
[68]	Rezaei and Kheirkhah, 2018	-	x	x						numerical ex.	F+R	MILP	↑	score	jobs, time	weights
[69]	Roni et al., 2017	-	x							bioeconomy	R	MILP	↑	jobs	jobs	-
[70]	Saffari et al., 2015	ISO	x							other	F+R	RPP	↑	jobs	jobs	-
[71]	Sahebjamnia et al., 2018	**GSLCAP**, SA, *ISO*	x	x						other	F+R	MILP	↑	score	jobs, time	weights
[72]	Samadi et al., 2018	-	x	x						numerical ex.	F+R	MILP	↑	score	jobs, time	weights
[73]	Santibanez-Aguilar et al., 2014	-	x							bioeconomy	F	MILP	↑	jobs	jobs	-
[74]	Santibanez-Aguilar et al., 2015	-	x							bioeconomy	F+R	MILP	↑	jobs	(unknown)	-
[75]	Sazvar et al., 2016	-	x							other	F	LP	↑	jobs (eq)	jobs	weights
[76]	Shokouhyar and Aalirezaei, 2017	LSR	x	x		x				EEE	R	MILP	↑	score	score	-
[77]	Silva et al., 2017	-					x			bioeconomy	R	MILP	↓	facilities (eq)	facilities (eq)	-
[78]	Soleimani et al., 2017	**ISO**		x					x	numerical ex.	F+R	P	↓ ↓	time, amount	time, amount	-
[79]	Teran-Somohano and Smith, 2019	-					x			waste mgmt.	R	P	↓	score	score	-
[80]	Tsao and Thanh, 2019	ISO, SA	x			x				other	F	MILP	↓	value (eq)	value, value (eq)	weights
[81]	Tsao et al., 2018	*ISO*	x	x				x		numerical ex.	F	FMILP	↑	score	jobs, time, hazardous	weights
[82]	Tuzkaya et al., 2011	-	x				x			EEE	R	P	↑	score	score	-
[83]	Varsei and Polyakovskiy, 2017	*GRIG3*	x			x				food ind.	F	MIP	↑	score	score	-
[84]	Yadollahinia et al., 2018	-							x	other	F+R	MILP	↑ ↓	score, distance	score, distance	-
[85]	You et al., 2012	-	x							bioeconomy	F+R	MILP	↑	jobs	jobs	-
[86]	Yue et al., 2014	-	x							bioeconomy	F+R	MILFrP	↑	jobs	jobs	-
[87]	Zahiri et al., 2017	-	x			x				medical ind.	F	FMILP	↑	score	jobs (eq), value (eq)	weights
[88]	Zhalechian et al., 2016	-	x			x				EEE	F+R	MINLP	↑	score	jobs (eq), value (eq)	weights
[89]	Zhang et al., 2016	-							x	numerical ex.	F	MILP	↑	amount	amount	-
[90]	Zhou et al., 2000	-							x	other	F	P	n.a.			
[91]	Zhu and Hu, 2017	**GRIG4**, *ISO, SA, ETI, FLA, UNGC*	x	x		x		x		EEE	F	P	↑	score	jobs (eq), time, value (eq), hazardous	weights

[1] **bold**: the article cites the framework including its categories (see Table 2) to justify the selection of specific aspects.
plain: the article cites the framework generally for the selection of aspects.
italic: the article cites the framework unrelated to the article's own work, e.g. as part of the literature section.
[2] detailed in the Supplementary material (M2a)
[3] forward supply chain (F), reverse supply chain (R), both forward and reverse elements (F+R)
[4] for nomenclature see Supplementary material (M1)

Appendix 3. Modelling features



Appendix 4. Nomenclature of objective functions and constraints

Parameter	Meaning	Variable	Meaning
cost	costs	FL	facility location
dev	development index/level	FC	facility capacity
dem	demand	FT	facility technology
dis	distance	HR+/HR−	hired/dismissed employees
edu	educational access	PT	product/material type
ecv	economic value	QI	quantity: inventory
gdp	gross domestic product (→ dev)	QP	quantity: production
haz	fraction of potentially hazardous products	QR	quantity: raw material
hrs	(working) hours	QT	quantity: transportation
job	number of jobs	QU	quantity: used products
ldd	lost days caused by work damages	SU	supplier selection
med	medical access level	TL	transportation link
nui	nuisance (e.g. visual pollution, social rejection, obnoxious effects)	TM	transportation mode
pop	population density		
sat	satisfaction		
sec	security level		
soc	social score (e.g. CSR, EPR, etc.)		
ump	unemployment rate		
was	generated waste		
(eq)	equivalents (e.g. jobs (eq), if jobs are being weighted by e.g. regional unemployment rate)		
(none)	no parameter; decision variable only		

Appendix 5. Social objective functions with social indicator and decision variables (DV)

Article	↑↓		*Social indicator*		*DV 1*	*DV2*	*DV 3*	*DV 4*	*DV 5*	*DV 6*
[01]	↑		*job*	×	*FL [FT]*	*QR [PT]*	*QP [FL,FT]*			
[02]	↑		*job*	×	*FL*					
[03]	↑		*job*	×	FL^{open}	$-\ FL^{close}$				
[09]	↑		*job*	×	*FL [FC,FT]*	*QR [PT]*	*QP [FL,FT]*	*QT [PT,TM,TL]*		
[23]	↑		*job*	×	*FL [FC]*					
[25]	↑		*job*	×	*FL [FT]*	*QP [FL,FT]*	*QT [FL]*	*QU [FL]*		
[38]	↑		*job*	×	*FL*	*SU*				
[39]	↑		*job*	×	*FL*	*FC*				
[40]	↑		*job*	×	*QP [FL]*	*QT [FL,PT]*				
[42]	↑		*job*	×	*FL [FC,FT]*	*QR [FL,PT]*	*QT [FL,PT]*			
[51]	↑		*job*	×	*FL*					
[53]	↑		*job*	×	*FL [FT]*	*FC [FL,FT]*	*QR [SU]*			
[55]	↑		*job*	×	*FL*					
[60]	↑		*job*	×	*FL*	*QT [FL]*				
[61]	↓		*job*	×	*FL*	*QT [FL]*				
[62]	↑		*job*	×	*FL*	*QT [FL]*				
[63]	↑		*job*	×	*FL [FC]*	*QR [SU]*	*QT [TL]*			
[69]	↑		*job*	×	*FL [FC]*	*QT [TL]*				
[70]	↑		*job*	×	*FL [FC,FT]*					
[73]	↑		*job*	×	*QP [FL,FT,PT]*	*QT [FL,PT]*				
[85]	↑		*job*	×	*FL [FC,FT]*	*FC*	*QR [PT]*	*QP [PT,FT]*	*QI [PT]*	*QT [PT,TM]*
		+	$job^{by\text{-}product}$	×	*QP [PT]*					
[86]	↑		*job*	×	*FL [FC,FT]*	*QP [FT,PT]*				
[05]	↓		$job^{required}$	×	$FC^{high\ dev}$ *[FL]*	$QR^{non\text{-}local}$ *[PT]*	$QP^{non\text{-}local}$ *[PT]*	*QI [PT]*		
		+	*(none)*		$HR^{+high\ dev}$ *[FL]*	$HR^{-low\ dev}$ *[FL]*				
		+	1 / $job^{available}$	×	FC^{idle}					
		+	$cost^{ldd}$ / $cost^{job}$	×	*QT [PT,TM]*					
[41]	↑		*(no explicit function given)*							
[43]	↑		*(no explicit function given)*							
[74]	↑		*(no explicit function given)*							
[75]	↑	w_1 ×	*(none)*		$HR^{+native}$					
		$-\ w_2$ ×	*(none)*		$HR^{-native}$	*(function incomplete)*				
[46]	↑		*job / pop*	×	*FL*					
[45]	↑		*job / pop*	×	*FL*	*FC [FL]*				

[48]	↓		dev^{GDP} / *job*	×	*FL*	*FT*	*TL*		
	↓	or	*ump / job*	×	*FL*	*FT*	*TL*		
[49]	↑		*job / pop*	×	*FL*				
[50]	↑		*job* / dev^{GDP}	×	*FL*	*FC [FL]*	*FT*	*QT [TM]*	*TM*
[07]	↕		*(+/−) hrs*	×	*QP [FL,FT,PT]*				
[13]	↑		*hrs*	×	*FL [FT]*	*QR [PT,SU]*	*QP [PT,FT]*	*QT [PT]*	
[14]	↓		*ldd*	×	*FT*				
[25]	↓		*ldd*	×	*FL [FT]*	*QP [FL,FT]*	*QT [FL]*	*QU [FL]*	
[78]	↓		*ldd*	×	*FL*				
[32]	↑		*job*	×	*FL [FT]*				
		−	*ldd*	×	*FL [FT]*				
[44]	↑		*job*	×	*FL*	*QP [PT,FL]*	*QT [FL]*		
		−	*ldd*	×	*QP [PT,FL]*	*QT [FL]*			
		+	*(none)*		$TL^{vehicles}$				
[65]	↑		*job*	×	*FL [FT]*	*FC [FL,FT]*			
		−	*ldd*	×	*FL [FT]*	*QP [FL]*			
[66]	↑		*job*	×	*FL [FT]*	*QP [FL,FT,PT]*			
		+	*(none)*		HR^{+}				
		−	*ldd*	×	*FL [FT]*				
[36]	↑	w_1 ×	*job*	×	*QP*				
		+ w_2 ×	1 / dev^{GDP}	×	*QP*				
[21]	↑	w_1 ×	*job*	×	*FL [FT]*	*QP [FL,FT]*	*QT [FL]*	*QU [FL]*	
		− w_2 ×	*ldd*	×	*FL [FT]*	*QP [FL,FT]*	*QT [FL]*	*QU [FL]*	
[68]	↑	w_1 ×	*job*	×	*FL*	*QP [FL,FT]*	*QT [FL]*	*QU [FL]*	
		− w_2 ×	*ldd*	×	*FL*	*QP [FL,FT]*	*QT [FL]*	*QU [FL]*	
[71]	↑	w_1 ×	*job*	×	*FL [FT]*	*QP [FL,FT]*	*QT [FL]*	*QU [FL,FT]*	
		− w_2 ×	*ldd*	×	*FL [FT]*	*QP [FL,FT]*	*QT [FL]*	*QU [FL,FT]*	
[72]	↑	w_1 ×	*job*	×	*FL*	*QP [FL]*	*QT [FL]*	*QU [FL]*	
		− w_2 ×	*ldd*	×	*FL*	*QT [FL]*	*QU [FL]*		
[81]	↑	w_1 ×	*job*	×	*FL [FT]*				
		− w_2 ×	*ldd*	×	*FL [FT,PT]*				
		− w_3 ×	*haz*	×	*QP [FT,PT]*				
[58]	↑	w_1 ×	*job*	×	*FL [FT]*				
		− w_2 ×	*ldd*	×	*FL [FT]*				
		− w_3 ×	*haz*	×	*QP [FT]*				
		− w_4 ×	*was*	×	*QP [FT]*				
[29]	↑	w_1 ×	*job* × *ump*	×	*FL [FC,SU]*				
		+ w_2 ×	*ecv* × (1 – *dev*)	×	*FL [FC,SU]*				
[87]	↑	w_1 ×	*job* × *ump*	×	*FL*				
		+ w_2 ×	*ecv* × (1 – *dev*)	×	*FL*				
[88]	↑	w_1 ×	*job* × *ump*	×	*FL [FC]*				

		+ w_2 ×	*ecv* × (1 – *dev*)	×	*FL [FC]*		
[59]	↑	w_1 ×	*job* × *ump*	×	*FL [FC,FT]*		
		+ w_2 ×	*ecv* × (1 – *dev*)	×	*FL [FC]*		
		– w_3 ×	*ldd*	×	*FL [FT]*		
		– w_4 ×	*haz*	×	*QP [FT]*		
[91]	↑	w_1 ×	*job* × *ump*	×	*FL*		
		+ w_2 ×	*ecv* × (1 – dev^{GDP})	×	*FL*		
		– w_3 ×	*ldd*	×	*FL [FT]*		
		– w_4 ×	*haz*	×	*QP [FT]*		
[04]	↑	w_1 ×	*ump* × *pop*	×	*QT [FL]*		
		+ w_2 ×	1 – *dev*	×	*QT [FL]*		
		+ w_3 ×	1 – *sec*	×	*QT [FL]*		
		+ w_4 ×	1 / *med*	×	*QT [FL]*		
		+ w_5 ×	1 / *edu*	×	*QT [FL]*		
[31]	↑	w_1 ×	*ecv*	×	*QP [PT]*		
		+ w_2 ×	*(none)*		*QU [PT]*		
		+ w_2 ×	1 / *dem*	×	*QT*		
		+ w_3 ×	soc^{EPR}	×	*FL*		
		+ w_4 ×	soc^{EP}	×	*FL*		
[03]	↑		soc^{MCDM}	×	*FL*	*QT [TM]*	
[06]	↑		soc^{MCDM}	×	*FT [FL]*		
[17]	↑		soc^{MCDM}	×	*FL*		
[20]	↑		soc^{MCDM}	×	*FL [FC]*		
[35]	↑		soc^{MCDM}	×	*QR [FL,SU]*	*QP [FL]*	*QT [FL,TM]*
[37]	↑		*soc*	×	*QT [FL]*		
[38]	↑		soc^{MCDM}	×	*QR [PT,SU]*	*QU [FL,PT]*	
[64]	↑		*sat*	×	*SU [PT]*	*TL [TM]*	
[76]	↑		soc^{MCDM}	×	*FL [FC]*		
[79]	↓		$nui^{max} – nui^{dis}$	×	*FL*		
[82]	↑		soc^{MCDM}	×	*QT [FL]*		
[83]	↑		soc^{MCDM}	×	*FL*	*SU*	
[84]	↑		*sat*	×	*QU*		
[22]	↑		*(no explicit function given)*				
[11]	↓		*dem*	–	*QT*		
[16]	↓		*(none)*		*QT*		
		/	*(none)*		*QP*		
[28]	↑		*(none)*		*QT*		
[52]	↓		*(none)*		*QR (from palm soil)*	*– QR (from food soil)*	
[78]	↓		*dem*	–	*QT*		
[89]	↑		*(none)*		*QT*		

[33]	↓		*pop × nui / dis*	×	*QT*		
[67]	↑		*cost / dis*	×	*QR [PT,SU]*	*QP [FL,PT]*	*QT [FL,PT]*
		+	$job^{required}$ × $cost^{wages}$	×	*QP [FL]*		
[80]	↓	w_1 ×	(*ump – job*) × $cost^{unempl}$	×	*FL*		
		+ w_1 ×	*job* × $cost^{immigration}$	×	*FL*		
		+ w_1 ×	$cost^{cargo}$	×	QT_1		
		+ w_2 ×	$cost^{cargo}$	×	QT_2		
[56]	↑		*(none)*		*FL*		
[47]	↑		1 / dev^{GDP}	×	*FL*		
	↑	or	*ump*	×	*FL*		
[77]	↓		pop^{dis} × *nui*	×	*FL [FT]*		
[24]	↑		*dis*	×	*FL*		
[84]	↓		*dis*	×	*QT*		

Appendix 6. Social constraints

Article	Term		Constraint	Primary objective(s)
[10]	*job × QU ± slack*	=	job goal	↓ total costs, ↓ emissions
[54]	*job × FL [FT]*	≥	lower limit for *job*	↑ profit
	ldd × FL [FT]	≤	upper limit for *ldd*	
[18]	$soc^{MCDM,deviation}$ × *QT [SU]*	≤	$soc^{MCDM,deviation}$ × *dem*	↓ total costs
[26]	soc^{MCDM} × *FL [FC]*	≥	lower limit for *soc*	↓ total costs
[27]	soc^{MCDM} × *FL [FC]*	≥	lower limit for *soc*	↓ total costs
[34]	*soc × FL [FC, PT]*	≥	lower limit for *soc*	↑ profit
[30]	$QT^{1G\ bioethanol}$	≤	QT^{total} × upper limit (%)	↑ profit
[90]	*QT*	=	*dem*	↑ profit, ↓ unrecoverable material + consumed energy, ↓ amount of hazardous waste, ↑ recovered materials & energy, ↓ pollution
[57]	dev^{GDP} × *FL ± slack*	=	social goal	↓ total costs, ↓ emissions
[08]	*(no explicit equations given)*			↓ total costs
[12]	*(no explicit equations given)*			↓ total costs
[15]	*(no explicit equations given)*			↑ profit + environmental credit
[19]	*(no explicit equations given)*			↓ total costs

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