Chapter 21
Progress for Life Cycle Sustainability Assessment by Means of Digital Lifecycle Twins — A Taxonomy

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Abstract To understand and optimize the impact of a product along its lifecycle, the consideration of social, economic and environmental factors is of increasing interest for customers and regulating institutions. In this context, Life Cycle Sustainability Assessment (LCSA) is used to monitor and understand the trade-offs of the three sustainability dimensions. Today, LCSA still faces major challenges, such as availability, actuality and validity of data or consistent and appropriate measures to support Design for Sustainability. New technological innovations may support the enhancement of the methodology. In the background of a digitized product and service lifecycle, especially Industry 4.0 technologies, Digital Twins and the integration of Artificial Intelligence may solve data and feedback challenges through new ways of data collection, transfer, validation and intelligent analysis. This paper aims at exploring this potential of new technological innovations for an enhanced LCSA of capital goods and durable consumer goods as well as related services and proposes a taxonomy. Therefore, a literature review to identify existing digital solutions and research gaps is established. For the identified gaps, a new concept, the Digital Lifecycle Twin for LCSA is presented. The authors address both, the positive but also the negative implications put on the LCSA framework from a sustainability perspective. Ultimately, these findings will contribute to the enhancement of the LCSA methodology as well as to the design of a support system to enable environmentally and socially sound design of products and services.

Keywords Life cycle sustainability assessment · Digitization · Digital solutions · Digital (lifecycle) twins · Artificial intelligence

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21.1 Introduction

The sustainability impact of products depends on the social, economic, and environmental implications caused throughout the lifecycle. Life Cycle Sustainability Assessment (LCSA) is used to monitor and understand the trade-offs between the three sustainability dimensions, providing customers, regulating institutions and decision makers with information on the sustainability performance of products. The results of the LCSA support legislators as well as decision makers during the product's life to optimize the sustainability of products or systems. Decision support systems use the LCSA results as an input and help, e.g. product designers, to make more informed and sustainable decisions. Nevertheless, this process does oftentimes not exhibit a continuous data flow and is very time consuming for users.

This paper aims at exploring the potential of new technological innovations for an enhanced LCSA of capital goods and durable consumer goods as well as related services. A taxonomy is developed based on a literature review to classify existing and future technologies, which aim at enhancing the LCSA.

21.2 Challenges of LCSA

On the way to a more efficient, dynamic and automated LCSA and sustainable decision-making, various challenges need to be addressed.

LCSA is the combination of Life Cycle Assessment (LCA), Social Lifecycle Assessment (S-LCA) and Life Cycle Costing (LCC) and consequently covers the three pillars of sustainability: society, economy and environment (Kloepffer 2008). The term LC(S)A is used within this paper to refer to the LCSA as well as its elements or only one element of the three (LCA, S-LCA or LCC). The LCSA mainly evolved from the classical LCA, the only standardized method. The LCSA process is structured into four phases: the goal and scope definition, the lifecycle inventory analysis (LCI), the impact assessment and the interpretation (DIN EN ISO 2006). Subsequently, the main challenges, which could be identified in literature, are presented for each phase in Table 21.1. These challenges are mainly identified based on (Kloepffer 2008; Guinée 2011; Finkbeiner et al. 2010; Neugebauer 2016). A consistent approach across all three pillars and the definition of system borders through all product lifecycle phases are crucial for the goal and scope definition. During the LCI and data collection phase, the most significant challenges are related to the availability of data and measurability of social parameters. The lack of consistent methods and the large range of indicators hinder the analysis and impact assessment. The key challenges for the interpretation and communication of the results is their complexity and the interdependency of design decisions and sustainability impact.

General challenges occur from the missing methodological consensus and standardization of the S-LCA framework as well as from the oversimplification of the LCC method with its limitation to economic costs and the negligence of broader

Table 21.1 LCSA phases and the identified main challenges

Definition of goal	
• Complex definition of consistent system boundaries with relevant inputs and outputs • Different types of reporting systems and methods for the LCA, S-LCA and LCC	• Lack of consideration of future dynamics in the common attributional modelling approach • Lack of holistic tools for the assessment
Life cycle inventory (LCI) and data collection	
• Data availability: limited economic data, lack of product specific data and company-external data exchange and fragmented representation of supply chains • Inconsistent data sources, especially when bridging the three dimensions • Inaccurate measurements of dynamics in indicators due to static method architecture and lack of actuality of data • Diverse data formats, data quality and context	• Questionable trustworthiness, granularity and quality of data • High effort for mainly manual data collection • No guarantee of secure data storage • Measurability of social indicators and regionalization of data (e.g. definition of fair wage) • Missing information for a holistic and robust future consequential modelling approach
Analysis and impact assessment	
• Lack of consistent impact assessment methods and characterization factors for the three dimensions	• Complex interconnection and dependencies of the different indicators representing LCA, LCC and S-LCA • No consensus on appropriate indicator sets
Deduction of measures and interpretation of results	
• Complex trade-offs and direct and indirect dependencies between the three dimensions • Challenge of automated and consistent deduction of measurements and feedback	• Complexity of identifying design dependencies between product design decisions and measured sustainability impact • Lack of real-time assessment and real-time support
Communication of results	
• No consideration of different types of communication channels (e.g. machine to machine, machine to human)	• Lack of providing individual and selected results tailored to specific groups of users • Complexity of LCSA results

economic aspects and impacts. The subjectivity of social data provides further challenges for the comparability of results derived for the different dimensions. This requires larger amounts of data. New technological innovations have the potential to address these challenges and support further enhancements of the LCSA methodology.

21.3 Literature Review

The execution of LC(S)A, especially the LCA, is supported by a wide range of digital software tools and databases. Current research is focusing on methodological improvements of the LCSA, but also on its technological support. First literature reviews with a focus on the use of Big Data, LCA and data collection have been executed (Mieras et al. 2019; Song et al. 2018; Cooper 2013). Nevertheless, a holistic review of progress of LCSA from a technological perspective is still missing.

Therefore, a systematic and extensive literature review is conducted to answer the following questions:

- Which current digital solutions exist for LCSA and how can they be categorized and clustered?
- Which challenges of LCSA do those digital solutions address and which may they solve?

21.3.1 Approach

The following steps were executed for performing the literature review:

1. Explorative search of relevant papers in the field of new technologies with the objective to enable progress in LC(S)A, which resulted in 10 papers,
2. Keyword analysis of these papers and categorization of abstracts, which led to the following clusters: (I) approach (LCA, LCC, S-LCA, LCSA) in focus and (II) technologies considered,
3. For each cluster, the sub clusters were identified and respective search strings defined. Cluster II includes the technological trends AI, Big Data, Blockchain, Cyber-Physical-System (CPS), Digital Twin (DT), and Internet of Things (IoT),
4. The respective search strings were defined and the search has been conducted in the database SCOPUS, which is one of the leading databases for scientific research.
5. The resulting papers (in total 180 papers) for each combination of search strings were then filtered for relevance and the abstracts of the remaining relevant papers (110 papers) were read and analyzed.

21.3.2 Results

The results of the literature review were analyzed in two steps. First, the overall number of papers per cluster and the papers with overlapping research topics from different clusters were identified. The overview is shown in Fig. 21.1. The nodes show the search term and the number of related papers in brackets. The number of papers, which treat two search terms is depicted on the edge between two nodes. The analysis of the sustainability assessment approach (cluster I, highlighted in green) shows that most papers focus on LCA. The total number of papers of a category may not be equal to the sum of the papers filtered by topic, since some papers deal with multiple topics.

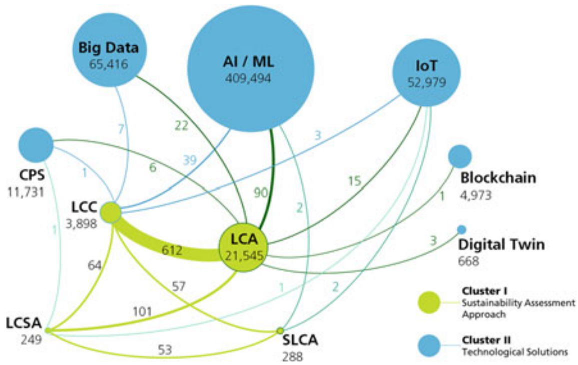

Fig. 21.1 Overview of the results of the literature review

As a second step, all papers, which are part of cluster I as well as cluster II, were filtered for relevance and analyzed in detail. For each category, a short analysis is presented in alphabetical order.

Artificial Intelligence (AI) or Machine Learning (ML)

A lot of research is conducted to improve sustainability assessment by means of AI (125 papers). Most of this research is focused on LCA (90 paper). Two papers also address S-LCA and 39 papers LCC, starting from 1997 with an uncertainty decision support system for gas turbine power generation (Gayraud and Singh 1997). After abstract screening, 48 papers are excluded from the further analysis, as they do not contribute new findings, such as to AI or sustainability assessment, or only present case studies. The remaining 77 relevant papers were analyzed in detail. A high amount of research focuses on the enhancement of decision support systems (46 papers) for specific domains in the planning phase. This includes planning of infrastructure projects, mainly water systems or road networks, product design, manufacturing or process planning and online optimization of maintenance or routing as well as the support for climate change strategies by legislators. Other research applies AI already in the LCI phase to enrich prediction of indicators in future lifecycle phases. Furthermore, AI-research focuses on support during the LCI phase and uncertainty considerations. Due to the high number of papers in this cluster, selected research is discussed exemplarily. Specific examples include multi-criteria decision-making and sensitivity analysis, which is addressed by e.g. using fuzzy reasoning (Chandrakumar et al. 2017). Other research addresses the decision support of product design by integrating LCA-tools into IT-systems from product development and by comparing product variants and their sustainability impact (Buchert 2019). An ant colony optimization-approach is used for sustainable product redesign by optimizing the assembly sequence (Ng 2018). Also, Product Lifecycle Management (PLM) systems are seen as important data source to enhance LCSA with AI (Karakoyun and Kiritsis 2014).

Big Data

28 papers focus on Big Data and LC(S)A, specifically LCA and LCC. Ten papers are not relevant for further analysis, because of only being a review paper (Song et al. 2018) or describing LCSA-case studies of Big Data applications. These are not considered further. Most of the research activities in the relevant papers on Big Data is closely linked to research in the field of AI, which can be explained by the fact that analysis of Big Data demands intelligent data analytic methods. In addition, there is an overlap with the research on DT. The identified research mainly presents Big Data in the context of building and construction projects, smart city or energy generation.

Blockchain

As a specific form of distributed ledger technology, blockchain is proposed by research as one possibility to increase data security. It can theoretically be applied for data collection and secure data storage, especially for sensitive social data, as well as for managing product-specific supply chain data (Abeyratne and Monfared 2016). However, the systematic review reveals only one paper by Smetana et al. specifically mentioning the application for sustainability assessment, namely the LCA (Smetana et al. 2018), which also integrates neural networks and CPS and can therefore be seen as a part of the AI and CPS research.

Cyber-physical Systems (CPS)

In total, only eight papers address CPS and sustainability assessment. One paper specifically considers LCSA with regard to the sustainability of CPS (Gürdür and Gradin 2017), but does not present CPS as a technological solution for LCSA execution. After filtering, only two papers are considered relevant for further analysis. Smetana et al. present a multidisciplinary research on CPS, AI and blockchain (Smetana et al. 2018). The authors discuss the theoretical applicability of blockchain and neural networks for LCA and material flow analysis. They propose an application in food production to monitor material flows. Vanderroost et al. propose a similar concept for food packaging based on data collection with CPS for LCA (Vanderroost 2017), but without AI-consideration.

Digital Twins (DT)

In general, "a Digital Twin is a digital representation of an active unique product [...] or unique product service system [...] that comprises its selected characteristics, properties, conditions and behaviors by means of models, information and data within a single or even across multiple lifecycle phases" (Stark and Damerau 2019). The review showed no research so far for DTs and LCSA. However, three papers propose approaches for combining DT and LCA. Barni et al. present a DT as an enabler for LCA with a focus on the manufacturing phase (Barni et al. 2018)—a topic of high relevance for this research. Also, Rückert et al. and Wellsandt et al. mention the DT for online LCA without detailing the concept (Rückert et al. 2018; Wellsandt 2017). Nevertheless, all research present the DT as a concept addressing all phases of a

LCA. They enable modelling of product lifecycles (Wellsandt 2017), collection of product-specific primary data via sensors and IoT-capabilities (Barni, et al. 2018), online-assessment (Rückert et al. 2018) as well as domain- and user-specific decision support (Barni et al. 2018; Riedelsheimer et al. 2018). A DT has the capabilities for automatic and autonomous decision-making up to action taking (Riedelsheimer et al. 2018), which can be used for decision support systems.

Internet of Things (IoT)

The search for IoT in the context of LCSA resulted in 18 papers with a main emphasis on LCA. After filtering, ten papers are considered as highly relevant, as they propose new technological solutions for the execution of LCSA (1), LCA (9), LCC (2) and/or SLCA (1). In the analyzed research, sensors are named as enablers for the collection of accurate, product-individual and actual data. Most of the papers focus on energy consumption during Begin of Life (BoL). A highly relevant approach for this research, is presented under the term ubiquitous Life Cycle Assessment by Raihanian Mashhadi and Behdad. The authors propose automated data collection during the manufacturing phase by using sensors and IoT-products on the example of a whole series of hard disc drives (Raihanian Mashhadi and Behdad 2018). Tu et al. propose an approach for a dynamic carbon footprint (CF) based on IoT-technology (Tu, et al. 2017). Garcia-Muiña et al. also use sensors and meters from a digitized production environment (Industry 4.0) as well as the input from manufacturing IT-Systems (MES) for a detailed impact analysis (Garcia-Muiña et al. 2018) in LCA, LCC and S-LCA. Brundage et al. present an analysis of sustainability methods for feedback to design with IoT from the manufacturing phase (Brundage 2018). The research by Kim et al. and Gu et al. focuses on the application of decision support in the End of Life (EoL) phase with data collection via sensors in the use phase (Kim et al. 2017; Gu et al. 2017). In addition, a new conceptual framework for IoT application in LC(S)A is developed by Tao, et al., who present a four-layer model using IoT-technology for data collection and integrating the bill of material (BoM) for data storage (Tao 2014). The solution aims to evaluate product individual energy consumptions along the whole lifecycle. The authors also discuss integration with existing enterprise IT-systems. In a similar approach Tao, Wang et al. present a framework for IoT (Tao 2016). A conceptual framework with different digital tools, that support along the lifecycle to optimize the sustainability of manufacturing systems, is proposed by Cerri et al. (2016).

Summary

In general, the literature review shows a wide scope of research for the application of different technologies in the framework of digitization and Industry 4.0. Against the background of a digitized product and service lifecycle, especially IoT-Technologies, CPS, DTs and AI may solve data and feedback challenges through new ways of data collection, transfer, validation and intelligent analysis. For example, automated data collection with sensors in the context of Industry 4.0 and IoT may supply current data for a real-time LCSA-execution. AI and semantics can be used to identify and analyze dependencies between indicators and support decision making.

21.4 Taxonomy and Gap Analysis

From the conducted literature review, a taxonomy is derived to classify existing and future technologies, which aim to contribute to progress for LCSA and the underlying methods. The aim of the taxonomy is to gain an overview and to assess the current state of research, industrial applications and the future vision for LC(S)A supporting technologies.

21.4.1 Approach

Based on the literature review, the taxonomy is developed and a gap analysis conducted by.

- **Abstract keywording**: Reading all relevant abstracts and extracting the main characteristics that describe the research results presented
- **Keyword clustering**: Grouping the extracted keywords to categories, such as scope, objective, subjective, type of product or phase of LCSA
- **Mapping**: the research findings from the literature review are mapped to the addressed phases of the LCSA and respective challenges (see chap. 2).
- **Gap Analysis**: At last, the gap analysis is conducted to identify unaddressed challenges in research and to derive research gaps for technological solutions.

21.4.2 Taxonomy

The resulting taxonomy with nine categories and respective options is shown in Fig. 21.2. Each technological solution, which aims at enhancing the LCSA execution, can be located within the proposed taxonomy. For each category, one option is chosen. Every combination of the different options is possible.

Subsequently all categories are shortly described:

(1) *Technology and* (2) *Characteristics of technology.*

In this category, the type of technology, which is presented as a solution, as well as its automatic and autonomous capabilities can be classified. This category will be extended with new technologies being developed and applied for LCSA.

(3) *Phase of LC(S)A and* (4) *Aspect of LCSA*

This category represents the traditional four phases of the LCSA-process (DIN EN ISO 2006) and an additional phase, the communication or feedback of the results to the respective user, which can be a human or an IT-system. In addition, it is necessary to specify the, which aspect of the LCSA the assessment is focused on.

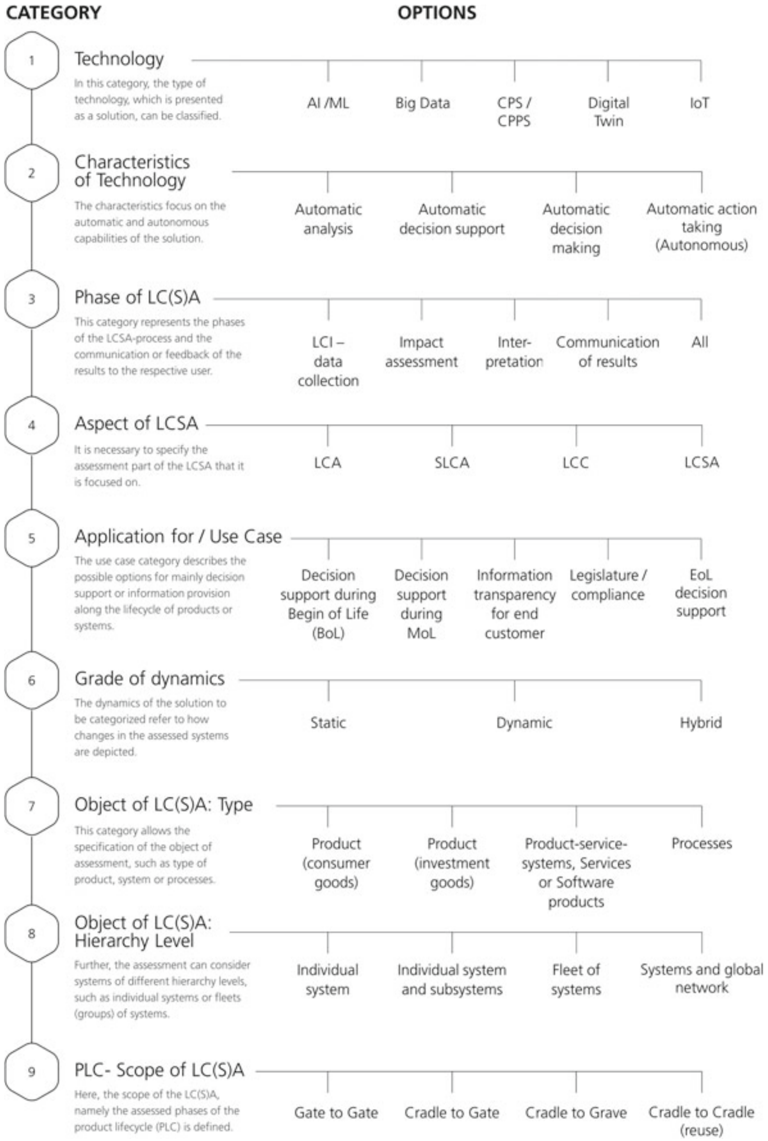

Fig. 21.2 Categories and characteristics of the taxonomy

Some solutions only integrate environmental (LCA), social (S-LCA) or economic (LCC) data.

(5) *Application for/use case*

The use case category describes the possible options of application, mainly decision support or information provision along the lifecycle of products systems. During BoL the product design, production planning or production decisions can be supported. In the Mid of Life (MoL) support for optimized operation, maintenance or information transparency for the end customer can be provided. Another use case is the support of legislation or compliance with regulation and thresholds as well as the decision support during EoL.

(6) *Grade of Dynamics*

The grade of dynamics of the solution refer to how changes in the assessed systems are depicted. Relevant are changes over time, individual systems in retrospective as well as future dynamics, such as changing behavior with changing environment and its prediction. Therefore, prediction algorithms are necessary to allow the representation of future dynamics. The collection of real-time primary data would allow a fully dynamic assessment.

(7) *Object of LC(S)A: type and* (8) *Hierarchy level*

These categories allow the specification of the object of assessment, such as type of product, system or processes. Further, the assessment can consider systems of different hierarchy levels, such as individual systems or fleet of systems, such as a fleet of vehicles for carsharing.

(9) *PLC-scope of LC(S)A*

Here, the scope of the LC(S)A, namely the assessed phases of the product lifecycle (PLC) is defined. An assessment can cover all processes starting from the cradle (raw material sourcing) or the production facilities (gate). The scope can include only the production phase (to gate), the use phase until the disposal phase (grave) or additionally the recirculation (cradle to cradle) (Barni et al. 2018).

21.4.3 Mapping and Gap Analysis

The gap analysis is conducted to understand the focus of current research and to identify research gaps with regard to the challenges of LC(S)A (see chap. 2). A special focus is put on the assessment of consumer goods and their complete lifecycle. For the gap analysis, the two main categories are plotted on the two axes: type of technology and the phases of the LC(S)A with its main activities (see Fig. 21.3). As a next step, all relevant research findings from the 110 papers of the literature review are located within the taxonomy. Blockchain is not considered in the analysis, because the only relevant paper is also part of the CPS and AI sub cluster. As some solutions focus on several phases of the LCSA-process, papers can be listed more than once. In total, 29 phase-specific and 3 generic challenges are defined in chap. 2. For each

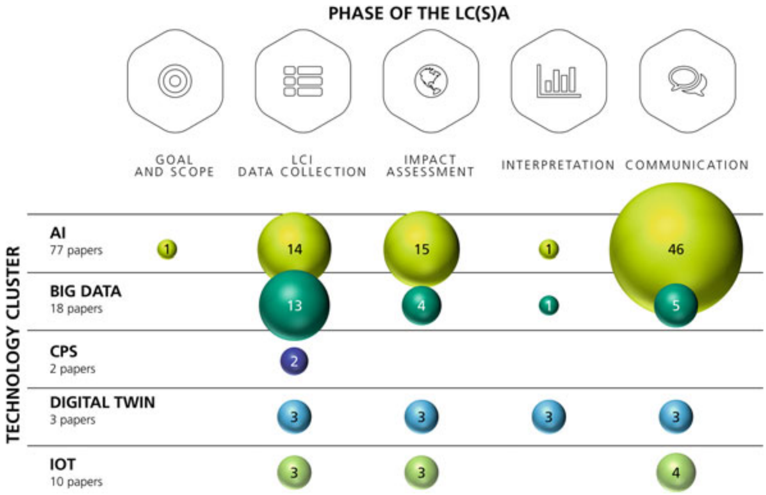

Fig. 21.3 Gap analysis for technologies and phases of LCSA

phase, it is analyzed whether the challenges are addressed in research and if they can potentially be solved by digital solutions or if they are mainly methodical challenges. Overall, the phase with the most research is the communication phase as well as the data collection for the LCI by means of Big Data and AI. Methodical challenges, that are not suited for automation, are not listed in the gap analysis, such as the definition of consistent system boundaries (goal and scope), lacking consideration of future dynamics in attributional modelling or lacking consensus on appropriate indicator sets. Consequently, the following unaddressed or only partially addressed technological challenges are identified:

- **Goal and scope**: Lack of holistic tools for the assessment
- **LCI and data collection**: Measurement of social indicators, incompleteness of supply chain data, lack of product specific data, inconsistent data sources, data formats, context and data quality, lack of actual data for depicting dynamics, highly effortful (partly manual) data collection, secure data storage, lack of company-external and EoL-data, missing information for consequential modelling
- **Analysis and impact assessment**: Lacking consistency of impact assessment methods between the three dimensions and indicator dependencies
- **Derive measures and interpretation of results**: Challenge of automated and consistent deduction of measurements and feedback, complexity of tradeoffs and dependencies between dimensions, complexity of identifying and quantifying design dependencies, lack of real-time assessment and support as well as unused potential of AI to enhance predictive LCSA
- **Communication of results**: Lack of providing individual and selected results tailored to specific groups of users, different types of communication channels

are not yet considered (e.g. machine to machine, machine to human), complexity of LCSA results is challenging to communicate

Additionally, the analysis shows that most applications in case studies are not covering the whole lifecycle (cradle to grave), but only parts of the lifecycle and therefore may disregard important impacts or aspects.

21.5 New Concept Digital Lifecycle Twin

A new concept for a Digital Lifecycle Twin (DLT) that is able to address these open challenges is presented subsequently. As a specific manifestation of the DT, the concept of a DLT is described by Riedelsheimer et al. (2018). Real-time lifecycle assessment is defined as a central use case of the DLT. Related work discusses the DT as an enabler for LCA (Barni et al. 2018) and specifically in the context of IoT (Raihanian Mashhadi and Behdad 2018). In addition, the research findings from the IoT cluster (Raihanian Mashhadi and Behdad 2018; Tu, et al. 2017; Garcia-Muiña et al. 2018; Brundage 2018; Kim et al. 2017; Tao 2014,2016) are seen as important input for the DLT concept.

The DLT addresses the following identified gaps (Chap 4.3) along the LCSA-phases with its key features:

LCI and data collection: Lack of product specific data, no automated data collection.

Analysis and impact assessment: Complex indicator dependencies of the different indicators representing LCA, LCC and S-LCA.

Derive measures and interpretation of results: Complexity of identifying design dependencies between product design decisions and measured sustainability impact, lack of real-time assessment and real-time support, challenge of automated and consistent deduction of measurements and feedback.

Communication of results: Lack of providing individual and selected results tailored to specific groups of users.

A DLT for LCSA is a specific form of a DT. A DLT for LCSA is the digital representation of a system, which collects and analyzes the sustainability information of the individual product's lifecycle from cradle to grave, specifically entailing a real-time, dynamic and product-specific LCSA. Figure 21.4 clarifies the relation of a DLT to different DT types as well as its context and use cases.

The specific vision for the DLT for LCSA is indicated by the location within the taxonomy (see Fig. 21.5). The DLT for LCSA must be able to automatically make decisions, integrates all aspects of sustainability (LCSA) and provides decision support during the BoL-phase.

A DT, according to Stark et al., consists of six different design elements (Stark et al. 2019), hardware, software, data repository, digital models and digital shadow data as well as intelligence. Accordingly, the necessary design elements of a DLT for LCSA are defined as follows.

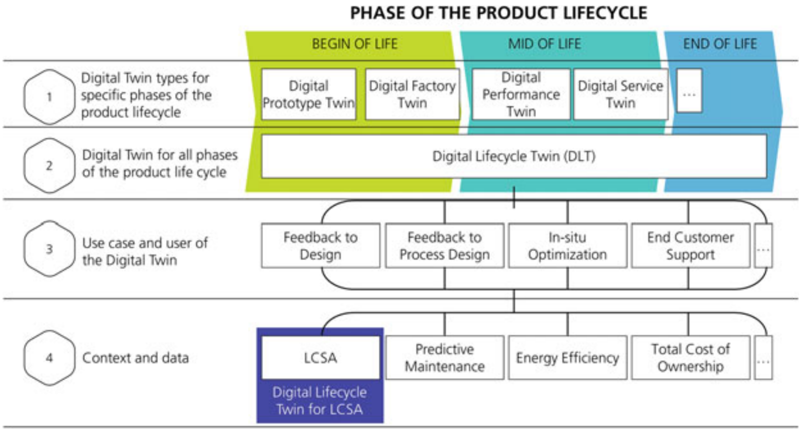

Fig. 21.4 Classification of the DLT

The DLT for LCSA integrates different technological capabilities, such as IoT and AI, and interconnects these along the lifecycle to gain insights on the current sustainability indicators of a system and to derive measures for decision makers within a narrow period. Therefore, a network of sensors near the physical system (soft- and hardware on the edge), IT-Systems (e.g. MES, ERP) as well as third party data sources are interconnected and deliver necessary actual data for the LCI and ultimately the LCSA-indicators. All the primary data is directly connected to the product or system in focus, the so-called Digital Shadow data. Edge devices collect, preprocess and transfer the Digital Shadow data, which is then stored in the DT data repository.

The impact assessment phase is enhanced by the integration of more data sources with actual data and the application of concurrent data analytics. The DLT for LCSA uses the Digital Master and Digital Prototype models from the planning phase to monitor and identify deviations of planned parameters and to draw inferences about necessary design changes and improvements. In addition to the Computer Aided Design (CAD)-models, different Bills of Material (BoM) describe the system on sub-system level including software configuration, manufacturing and service information. On this basis, a decision support system for product design can be implemented.

In summary, the DLT for LCSA can be seen as a real-time decision support system for different decision makers along the lifecycle of a product. By integrating more primary and actual product-individual data in addition to the commonly used secondary data, a better data and information basis for automatic decision making or even a partly autonomous system could be achieved.

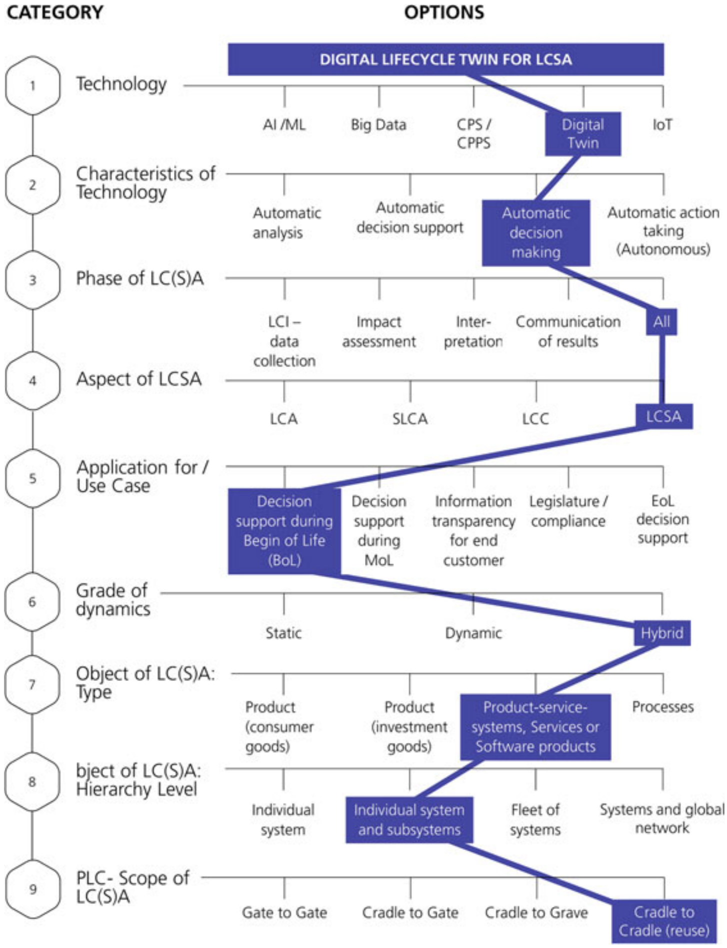

Fig. 21.5 Allocation of the DLT in the taxonomy

21.6 Sustainability Impact and Conclusion

The authors conducted an extensive systematic literature review to identify existing research on technological progress for LCSA. Within a gap analysis, unaddressed challenges are identified and a new holistic concept—the DLT for LCSA—is proposed as a solution to address selected gaps. The goal of the presented DLT is the enhancement of LCSA by increasing information transparency and provision of real-time information on the sustainability of a system. Additionally, by supporting product design decisions, the DLT targets the improvement of the products sustainability performance. However, to evaluate the sustainability improvements, the sustainability impact of the DLT itself needs to be assessed. Due to the fact, that there is no known implementation of a DLT for LCSA, there is also no data basis for an assessment. Questions to be answered in this context are: Can LCSA be applied to an underlying DLT system? Which specific characteristics need to be taken into account? As a DLT is not solely a hardware neither a software product, different requirements might arise. If a DLT is defined as a CPS, the LCSA of a CPS can be used for guidance (Gürdür and Gradin 2017). Other orientations could be LCSA of Product Service Systems (PSS) (Peruzzini and Germani 2013), if a DLT is understood as a system of a physical product and accompanying services.

Future research steps should focus on the elaboration of the DLT concept as well as the sustainability assessment of DLT implementations. In particular, the applicable data structure and information content as part of the DLT for LCSA needs to be defined. Furthermore, existing solutions for integrated and automated decision support should be examined against the adaptability for LCSA. Ultimately, these findings will contribute to the enhancement of the LCSA execution as well as to the design of a support system to enable an environmentally and socially sound design of products and services.

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