Visual Analytics Tools for Sustainable Lifecycle Design: Current Status, Challenges, and Future Opportunities

Devarajan Ramanujan[†,*], **William Z. Bernstein**[⁎], **Senthil K. Chandrasegaran**[♣], **Karthik Ramani**[✦]
[†]Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139
[⁎]Systems Integration Division, National Institute of Standards & Technology, Gaithersburg, MD 20988
[♣]College of Information Studies, University of Maryland, College Park, MD 20742
[✦]School of Mechanical Engineering, Purdue University, West Lafayette, IN 47907
Email: devr@mit.edu, wzb@nist.gov, senthilc@umd.edu, ramani@purdue.edu

The rapid rise in technologies for data collection has created an unmatched opportunity to advance the use of data-rich tools for lifecycle decision-making. However, the usefulness of these technologies is limited by the ability to translate lifecycle data into actionable insights for human decision-makers. This is especially true in the case of sustainable lifecycle design (SLD), as the assessment of environmental impacts, and the feasibility of making corresponding design changes, often relies on human expertise and intuition. Supporting human sense-making in SLD requires the use of both data-driven and user-driven methods while exploring lifecycle data. A promising approach for combining the two is through the use of visual analytics (VA) tools. Such tools can leverage the ability of computer-based tools to gather, process, and summarize data along with the ability of human-experts to guide analyses through domain knowledge or data-driven insight. In this paper, we review previous research that has created VA tools in SLD. We also highlight existing challenges and future opportunities for such tools in different lifecycle stages—design, manufacturing, distribution & supply chain, use-phase, end-of-life, as well as life cycle assessment. Our review shows that while the number of VA tools in SLD is relatively small, researchers are increasingly focusing on the subject matter. Our review also suggests that VA tools can address existing challenges in SLD and that significant future opportunities exist.

1 INTRODUCTION

Reducing the environmental impacts of products and services is now an important focus for industries [1]. With the ever-increasing complexity of production and consumption systems, it is imperative for industries to harness knowledge from every phase of the lifecycle to create more sustainable products and services.

The arrival and emergence of information technologies, such as the Internet of Things (IoT), cloud computing, and cyber-physical systems, is pegged to herald a fourth industrial revolution (often termed as Industry 4.0 [2]). Industry 4.0 is expected to create knowledge vital for enabling data-driven approaches to sustainable lifecycle design (SLD) [3]. While such technologies have the potential to significantly advance the use of data-rich tools for decision-making in SLD, their usefulness is limited by the ability to translate lifecycle data into actionable insights for decision-makers [4]. To illustrate, a report by the McKinsey Global Institute [5] states that the manufacturing sector alone stores close to 2 Exabytes of new data, a figure from 2010. However, it is widely accepted that until now, the manufacturing world is far from effectively using this data and meeting its true potential in the digital age [6]. Considering that manufacturing represents only a fraction of the total data generated throughout the lifecycle, other data sources such as customer feedback from web surveys, use-phase resource consumption data from on-board sensors, and recycling rate reports, compound the challenge of translating data to knowledge for use in SLD.

Addressing this challenge requires new approaches for collecting, structuring, analyzing, and presenting lifecycle data in a manner that is useful for decision-makers. To this end, our paper reviews the motivation, current status, challenges, and future opportunities for visual analytics (VA) tools—that combine data-driven approaches for data analysis with user-driven methods for data exploration—in the context of SLD. To clarify, in this paper, SLD is defined as the process of designing every lifecycle stage of a product to minimize its environmental impact. We specifically focus on the environmental dimension of sustainability due to large number of previous works discussing relationships between lifecycle decision-making and the resulting environmental impacts. Here, we begin our discussion by giving a brief overview of VA and its use in SLD.

VA differs from existing approaches to complex data

*Address all correspondence to devr@mit.edu

analysis in that it augments the most appropriate data analysis algorithms for a given application area and goal with human perception through the use of interactive visualizations. VA has a number of definitions depending on its context of use. It is broadly defined by Thomas and Cook [7, p. 5] as "the science of analytical reasoning facilitated by interactive visual interfaces". It is important to note the distinction from visualization, which is defined as the "use of computer-based, interactive visual representations of data to amplify cognition" [8, p. 7]. Visualization subsumes the fields of information visualization (where the data is nonphysical) and scientific visualization (where the data is physically based). Keim et al. [9] in their definition, explain how information visualization is part of VA: "Visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making on the basis of very large and complex data sets" [p. 157].

VA achieves its goal through a sense-making loop where analysts use interactive visualizations for exploring results of an initial analysis, then use their perception to gain further insights into the data, guiding further analysis. This results in a progressive loop of analysis, visualization, perception, and insight, which ultimately guides the analyst to form and test hypotheses. Key application areas wherein VA has found prominent success include business intelligence, medicine, emergency management, physics, astronomy, and weather monitoring [10]. Each one of these domains requires collecting, processing, and visually summarizing sizable, disparate data. As an example from the business intelligence domain, the 300 million credit card transactions per day introduce significant complexity in analyzing data under multiple perspectives and assumptions across changing historical and current situations [10]. Foreseeing similar situations in product lifecycle management (PLM), Keim et al. [9] suggest that VA may be used in engineering for analyzing complex data that arises from design, production, and feedback from product use. Bras [11] acknowledges that methodological tools for decision support in environmentally conscious design require effective integration in terms of gathering, managing, analyzing data, and helping users assess the environmental impacts of their design decisions–which forms the essence of data-driven design. VA can be especially useful for aiding decision-making in SLD in light of these existing challenges. To this end, our paper aims to identify future research directions needed to create VA tools that can be applied to real-world problems in SLD.

2 MOTIVATION

The decision-making process in SLD is complex because of ambiguities present in design representations, lack of information from downstream life cycle stages, and uncertainties in environmental assessment [12]. These issues make it challenging to quantitatively predict relationships between products' attributes and their environmental impacts [13]. The growing trend towards product digitization and the environments in which they operate make it increasingly possible to address these challenges through the use of data-driven approaches [14]. Fully and semi-automated approaches based on techniques such as data mining, neural networks, automated concept generation, and expert systems have been developed [15–19]. Automated approaches for SLD are prone to limitations faced by other knowledge-intensive systems in design, e.g. lack of flexibility and the high cost of development and maintenance [20]. This motivates the use of tools that augment human expertise rather than completely replacing them [21].

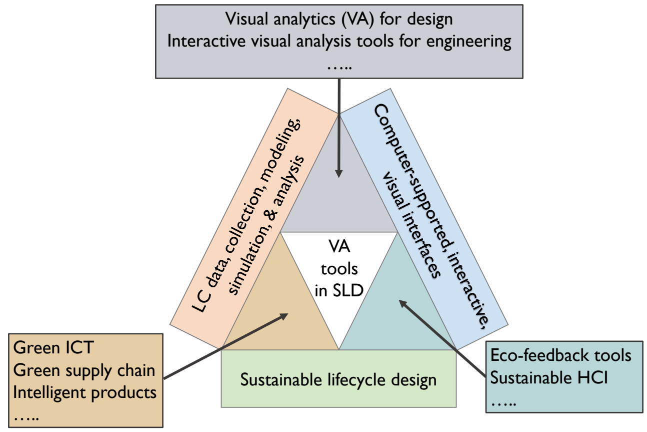

Fig. 1. Creating visual analytics (VA) tools for sustainable lifecycle design (SLD) requires research in (1) sustainable lifecycle design, (2) data-driven approaches for lifecycle data collection/analysis, and (3) computer-supported, interactive, visual interfaces.

As humans are often an integral part of decision-making processes in SLD, it is necessary to support *sensemaking*—structuring the unexpected or the unknown [22]—during data exploration and analysis tasks. According to Rizzoli and Young [23], environmental systems present unique challenges as they carry distinct features: dynamics, spatial coverage, complexity, randomness, periodicity, heterogeneity, and paucity of information. These added complexities further motivate the need for sensemaking processes in SLD. Addressing these challenges require the use of both, data-driven methods (that gather, process, and summarize the data) as well as user-driven methods (that allow users to input their domain knowledge or data-driven insights) while exploring lifecycle data. A promising approach for combining the two is through the use of VA tools [24]. VA tools combine the powerful pattern detection properties of the human visual system with the large data processing and manipulation capabilities of a computer system [25]. This allows such tools to support designers' insight generation processes and leverage their expertise in qualitative decision-making. As noted earlier, VA has been successfully applied in domains such as business intelligence, emergency management, and weather monitoring [10], which like SLD, need decision-makers to work with sizable, disparate data. Thus, VA tools have the potential to augment existing approaches for decision-making in SLD.

Figure 1 illustrates the primary domains underlying VA tools for SLD. Creating such tools is an interdisciplinary task that bridges (1) data-driven approaches for lifecycle data col-

Table 1. List of keywords used to identify papers relevant to VA tools for SLD. All combinations of search strings formed by selecting 1 keyword in the sustainability domain and 1 keyword in the visualization domain were used as queries. For example, one query in the design stage was, "sustainable design" (AND) "visual analytics". The only exception to this rule was the end-of-life stage in which 2 domain keywords were coupled with 1 visualization keyword, e.g. "end of life" (AND) "sustainable" (AND) "data visualization".

LC Stage	Domain Keywords	Visualization Keywords
Design	{eco design, sustainable design, environmentally conscious design, eco conscious design, green design, design for environment}	{visual exploration, visual analytics, information visualization, data visualization}
Manufacturing	{sustainable manufacturing, eco conscious manufacturing, environmentally conscious manufacturing, environmentally benign manufacturing, green manufacturing}	{visual exploration, visual analytics, information visualization, data visualization}
Supply chain	{sustainable distribution, sustainable supply chain, green supply chain}	{visual exploration, visual analytics, information visualization, data visualization}
Use-phase	{sustainable use, ambient display, persuasive computing, eco feedback}	{visual exploration, visual analytics, information visualization, data visualization}
End-of-life	{end of life, reuse, remanufacture, upgrade, recycle, disassembly, take back, recovery} & {sustainable, green, eco conscious, environmentally conscious}	{visual exploration, visual analytics, information visualization, data visualization}
Life cycle assessment	{life cycle assessment, life cycle analysis, LCA}	{visual exploration, visual analytics, information visualization, data visualization}

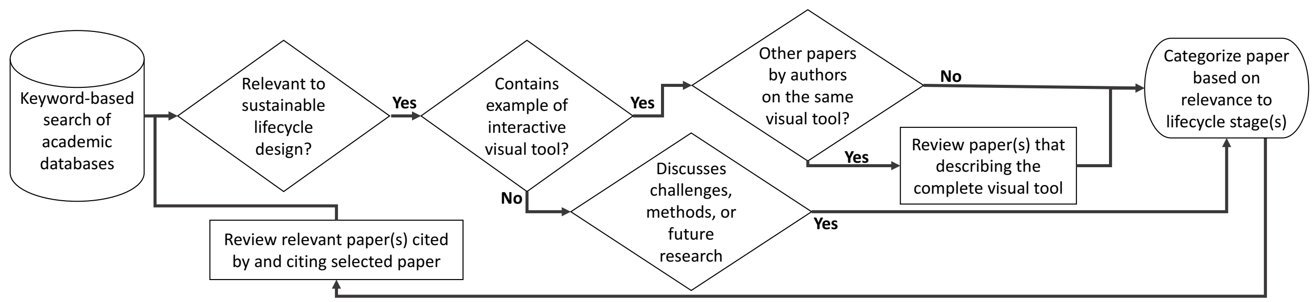

Fig. 2. Decision-making approach for filtering papers obtained from the keyword search.

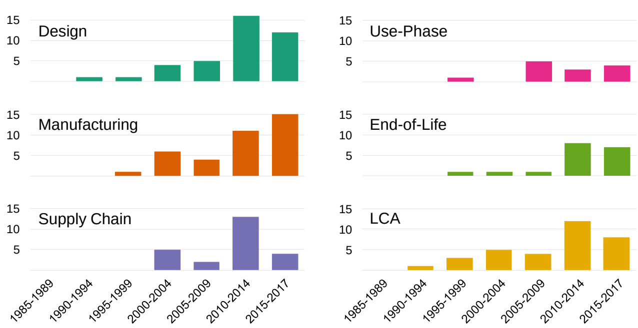

Fig. 3. Histograms illustrating publication years of 164 papers (categorized by lifecycle stage) left after the filtering process.

lection, modeling, simulation, and analysis, (2) creation of computer-supported, interactive visual interfaces for presenting lifecycle data, and (3) application of domain knowledge from sustainable lifecycle design.

Though VA tools present significant potential for facilitating better decision-making in the context of environmental sustainability, their methods and practices are not void of their own challenges in implementation and dissemination. One study [26], in particular, distills out practical challenges and barriers experienced during a 3.5 year academic-industry collaboration that aimed to deploy integrated VA tools in a large automotive company. Our paper discusses similar anticipated challenges in delivering practical VA tools for SLD.

3 REVIEW METHODOLOGY

To identify VA and visualization tools in SLD, we conducted a detailed review of previous literature. First, we formulated a list of search keywords based on our knowledge of previous work. We added search keywords to the original list as we found alternate terminology used in papers from the search results. Table 1 lists the final set of keywords used. Papers were identified through online academic databases, including Google Scholar Search, Scopus, Engineering Village, Web of Science, and the ASME digital collection. These databases were chosen as they index a wide range of journals, books, and conference proceedings in engineering. Restricting our search to these databases may have resulted in us missing significant previous work. However, we believe that the breadth of articles returned is representative of the area. In total, 367 publications were obtained from the keyword search process.

Figure 2 shows the decision flowchart used for filtering papers. At the first decision point, results were analyzed to verify their relevance to SLD and VA. This was done through an analysis of the paper title, abstract, and mentioned key-

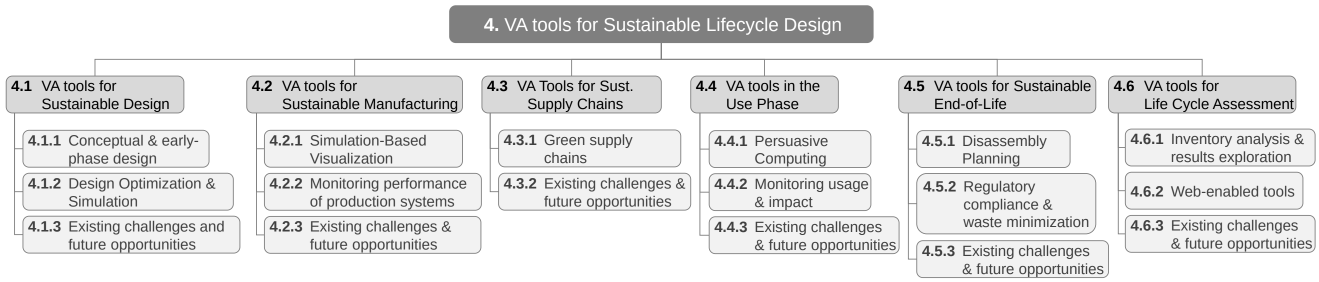

Fig. 4. Graphical view showing the organization of Section 4. As shown, the review of VA tools for SLD is split into subsections that follow the stages in the product lifecycle—from design to end of life. VA tools for LCA are also reviewed. Each lifecycle stage is further divided into sub-themes based on the type and number of tools that we found in our literature survey. Each subsection ends with a discussion of relevant current challenges and future opportunities.

words. Next, we checked if the resulting papers contained examples of computer-supported, interactive visual tools relevant to SLD. If they did not contain such a tool, we checked if the paper discussed methods for creating such tools, challenges in creating such tools, and future opportunities or research directions. We also checked if the same authors published other work on the same visual tool. If so, we only discuss the paper with the most comprehensive description of the tool in our review.

Finally, the paper is classified based on its relevance to a lifecycle stage. As shown in Table 1, the lifecycle stages include design, manufacturing, supply chain, use-phase, and end-of-life. These specific lifecycle stages were chosen based on the classification by Ramani et al. [12]. We added two other stages—use-phase and life cycle assessment (LCA) as we found previous research also discusses information visualization and VA tools specific to these contexts. If a lifecycle stage did not have any significant work that met this criterion, we expanded the scope to papers visualization approaches that can potentially be used to create VA tools. Methods such as machine learning, expert systems, and data mining have also been used to promote sustainable design [15–17], manufacturing [27], supply chains [28], and end-of-life [29]. We do not classify such works as VA tools as they do not explicitly include means for the visual analysis and exploration of data. In total, 164 publications were obtained through our filtering. These publications relate to previous VA tools in SLD, methods for creating such tools, challenges in creating such tools, and potential research directions. Figure 3 illustrates the publication year of these papers. They are categorized based on lifecycle stages in Table 1. As shown, the rising number of publications seems to be indicative of an increasing interest in this research area.

In the papers that were filtered out, we found that one set of papers used common, static visualizations (such as bar charts) to display lifecycle data relevant to SLD. Another set of papers discussed new visual representations for lifecycle data. These papers are not included in our review as they did not discuss the creation of computer-supported interfaces that could use the visual representations. Finally, the largest set of papers filtered corresponded to computer-supported visual tools that were not directly related to SLD. Such papers were obtained in our search as they mentioned sustainability in discussions not central to the paper's theme.

4 VA TOOLS FOR SUST. LIFECYCLE DESIGN

Here, we discuss previous research that has created visual analytics (VA) and visualization-focused tools in sustainable lifecycle design (SLD). Our review focuses on identifying the kinds of tools created, the challenges in creating them, and the research that must be conducted to improve their adoption and dissemination in research and practice. We classify the discussed papers based on the lifecycle stages to which they are most applicable. As shown in Fig. 4, the review of VA tools for SLD is split into subsections according to lifecycle stages mentioned in Ramani et al. [12]. VA tools for use-phase and life cycle assessment (LCA) are also reviewed. Each lifecycle stage is further divided into sub-themes. For example, in the design stage, we discuss VA tools for SLD in the context of (1) conceptual and early-phase design, and (2) design optimization and simulation. The sub-themes were created based on the type and number of tools that we found in our literature survey. Each subsection (i.e. VA tools for sustainable design) ends with a discussion of relevant current challenges and future opportunities. We have attempted to organize these sections in a modular fashion, so that readers interested in a particular topic can easily locate relevant references. Section 5 presents a more holistic view and details the future research needed for promoting VA tools in SLD.

4.1 VA Tools for Sustainable Design

The use of visualization in design is mostly driven by the need to (1) characterize and navigate multi-dimensional design spaces [30], (2) understand parameter trade-offs for design optimization [31–33], and (3) generate insights, patterns, and trends for decision-making [34, 35]. Thus, visualization finds application in design for both scientific visualization (SciVis) and information visualization (InfoVis). Card et al. [8] distinguish the two methods in that *SciVis* typically applies to scientific and physically-based data, e.g. engineering stress and fluid velocity, while *InfoVis* applies to abstract, non-physically based data, e.g. parameter spaces and product/supply chain structures. VA tools for design simulation often rely on SciVis for enabling visualization of physical parameters [36]. Such tools are widely used in sustainable building design for exploring energy use, daylighting, and thermal management [37]. VA tools used earlier in the sustainable design process often focus on facilitating parameter and design space exploration. Design parameters and environmental indicators lack physical dimensionality and thus do not have unique mappings to visual representations. A wide range of standard and custom visualization methods are used in previous work to support such processes. Interested readers are directed to works by Chi [38] and Keim [39] that present taxonomies for data visualization.

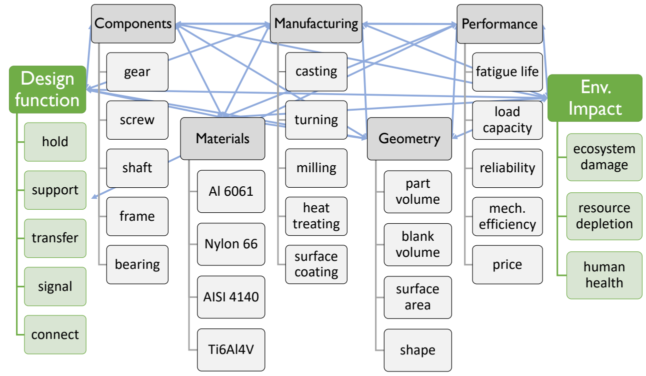

Fig. 5. While a product's environmental impact is a consequence of parameters chosen in early design, explicitly relating the two is a challenge. Sustainability-focused exploration of design spaces requires approaches that can dynamically link complex, multi-modal, multiply-related data.

4.1.1 Conceptual and early-phase design

In the initial stages of design, although the end goal is known, designers rarely know the best approach for the problem, what questions to ask, and which among them are the right questions to consider. Therefore, it is important to facilitate reuse of previous information and exploration of design spaces at this stage for aiding sustainable design [12].

Previous research in creating VA tools for early design has looked at (1) facilitating exploration of 3D part repositories for eco-conscious decision-making [40], (2) solution finding using the theory of inventive problem solving (TRIZ) for helping designers transform the most impactful flows from LCAs into potential flows for eco-improvement [41], (3) relating LCA results with design using visualization and dynamic interfaces [42], and (4) predicting energy usage & carbon emissions for visual exploration of buildings [43]. The developed VA tools facilitate the following:
1) *Relating results from environmental assessment to design attributes in previous products:* Such efforts can help reduce disparities between data representations used in environmental assessment and those used in early design. This disparity has been identified as a challenge for current eco-design tools [44]. Addressing this gap is vital for aiding environmentally-benign design of new products.
2) *Simultaneously exploring design and sustainability related information in large, complex decision spaces:* This is achieved using visual overlays or through linking visual representations [45]. When evaluating shapeSIFT with designers, Ramanujan et al. [46] mention that visual overlays help designers better understand relationships between sustainability and design attributes by allowing them to trade materials, manufacturing processes, and part functions.
3) *Discovering a suitable redesign strategy by evaluating the impact of design changes:* For example, assessing the effect of material or manufacturing process substitution, geometry change, on the environmental performance of a design.

4.1.2 Design optimization and simulation

Computer-aided tools for parametric design, simulation, and optimization find extensive use in design. The large amounts of data generated by such tools makes them amenable for VA. The fields of building design and urban planning have used VA tools for aiding sustainable design [37, 47]. Examples include (1) collaborative decision-making of in-fill development in cities [48], (2) design, control and implementation of adaptive lighting [49], (3) integration of daylighting considerations into building design [50], (4) regional energy planning [51, 52], (5) optimization of building elements reusability [53], and (6) design & management of sustainable data centers [54]. The design methods used in these domains may differ from those adopted in product design. Even so, the underlying methods for creating such tools, visual representations, and the interaction frameworks, can inform researchers creating VA tools for SLD in the context of product design.

Interactive visual analysis tools have been explored in the context of mechanical engineering [36]. It can be argued that VA tools in mechanical design address sustainability through applications such as, engine design for reducing emissions, computational fluid dynamics analysis of automobile design, or use-phase energy simulation of electronics. However, the lack of simultaneous visualization of environmental indicators with design parameters can prevent designers from gaining insights about the impact of a design change on the overall environmental impact of the product. For example, understanding the environmental benefit from an engine design that uses 5% more aluminum but produces 0.01% less carbon dioxide emissions is quite complex. Additionally, it can also prevent designers from trading off design parameters for realizing a globally optimal design with regards to environmental sustainability. The barriers towards creating VA tools of sustainable design in such applications include translating design attributes to inventory parameters, automatically quantifying environmental impacts during simulation or optimization runs, developing environmental indicators that are understandable by designers, and enabling the reusability of visualization and interaction models for design and sustainability-related data.

4.1.3 Existing challenges and future opportunities

One of the most significant constraints to creating VA tools for sustainable design is the limited amount of data available during early design. To address this challenge, researchers have to look at approaches for projecting lifecycle information back to the design stage [12]. As shown in Fig. 5, the relationship between design variables (particularly in early design) and the consequent environmental impacts is challenging to explicitly quantify. This is because the computation of environmental impacts depends on multiple interrelated parameters such as design function, geometry, materials, and manufacturing processes. Significant research opportunities exist in relating results from environmental assessment of similar products back to design. The increased use of digital interfaces for collecting product-related data across its entire lifecycle will also help in this endeavor.

Another challenge is the ability to create representations for products that promote exploration of design spaces and product attributes. The design stage uses multiple representations of products, including function trees, sketches, physical prototypes, and computer-based models. Also, current representations of product lifecycle data are not universally standardized [55]. Thus, VA tools for sustainable design must contend with heterogeneous data from a wide variety of sources. To this end, there has been a recent push to create standards for gathering and modeling lifecycle data [56–60]. These standards efforts have been met with great challenges themselves. One significant barrier is formally representing knowledge and lifecycle information models. A proposed solution is the formal ontology-based representation of product data through OntoSTEP [61]. Future research can look at utilizing such efforts to create VA tools for sustainable design.

The rise in consumer demand for green products coupled with the ability for techniques such as ubiquitous sensing and crowdsourcing to gather user needs in large volumes will also drive the need for novel VA tools in sustainable design. Such tools will be needed to help designers gain insight into the needs, perceptions, and preferences of end users and to translate these insights into design attributes [62–64].

We also envision improvements in environmental assessment, such as improved model & data separation, more automation, and better integration with computer-aided engineering tools, will help develop VA tools for sustainability-focused design optimization and simulation. Here, a promising use case for VA tools is aiding designers gain insights about design changes that can reduce the environmental impacts of products and processes from large-scale simulation results. Another potential application for VA tools is studying the sustainable design process itself to better understand designer behavior [65].

4.2 VA Tools for Sustainable Manufacturing

One of the earliest, most widely studied uses of InfoVis in manufacturing is the process control chart, first proposed in 1932 by Walter Shewhart as a general statistical technique to make sense of individual process samples [66]. Significant advances have occurred since then. Today, production facilities commonly process data codified in visual variables, e.g. position and color, to represent different system states and track particular key performance indicators (KPIs) [67]. Focused on improving scheduling and manufacturing sequence management, Sackett et al. [68] classified opportunities for graph-based visualizations of production facilities under the InfoVis techniques classification by Keim [69].

Though most VA tools for manufacturing are developed in-house by large manufacturing companies, there have been some published prototypes. Matković et al. [70] presented TTPView 3.0, which was designed to visualize manufacturing processes at varying levels of detail depending on the user and goals of the analysis. Mazumdar et al. [71] proposed a knowledge-based visualization dashboard that allows users to quickly identify problems on the manufacturing floor by querying a large collection of documents from disparate sources. ViDX [72] was an interface developed to deal with the significant velocity of data streams from production facilities. In ViDX, users can aggregate various levels of data with automated anomaly detection that is already embedded in the system. This interaction allows users to focus on specific disruptions in the production facility, such as significant energy consumption of a single or set of processes. Similarly, LiveGantt [73] uses data aggregation and codification schemes to present a large amount of streaming information of a production facility in a packaged view primarily using horizon graphs [74]. None of these tools explicitly track environmental aspects of a production system. However, extending these tools to include analytics on environmental indicators is a viable future research direction. Researchers and practitioners are working towards extending related methods specifically in the context of environmental sustainability [59, 60, 75]. With the availability of more intuitive and open tools for statistical learning, such as predictive analytics, there is a clear opportunity for integrating them with VA tools for sustainable manufacturing.

In this section, we focus on works that aid in improving the environmental sustainability of production systems from two primary perspectives: (1) simulation-based visualization, and (2) process-based performance monitoring. A more general overview of the use of visualization in manufacturing, can be found in the review by Esmaeilian et al. [76].

4.2.1 Simulation-based visualization

Simulation-based visualizations have provided key insights for tracking sustainability aspects of manufacturing processes [77, 78]. Wenzel et al. [79] presented a taxonomy of visualization techniques for simulation in production systems. Langrana et al. [80] illustrated the use of simulation visualization to optimize control parameters for environmental performance in the context of fused deposition methods. Herrmann et al. [81] presented a visualization dashboard tracking an energy oriented simulation model to aid in planning and better controlling manufacturing systems. Another prototype allows users to compose eco-assessment models of unit manufacturing processes and compute overall emissions, energy consumption, and waste [82]. In the process composition interface, users change parameter variables associated with models and modify process sequence to test environmental performance of different states and configurations. The SIMTER tool provides a rich interactive simulation environment, wherein users experiment with various factory layout configurations and quickly understand advantages of one design to another with respect to environmental performance [83]. This work was extended to provide a VA-based perspective using a Gantt chart as the primary interaction [84]. Changing parameters, e.g. time associated with a single stage in a string of processes, holistically shows propagated effects across the factory layout. Wörner et al. [85] presented a similar system that allows user interaction in the visual analysis of an advanced manufacturing simulation.

4.2.2 Monitoring performance of production systems

A prominent development in this area is the deployment of visualization dashboards to monitor manufacturing process performance. Some of these solutions also include platforms that provide additional intelligence based on the collected shop-floor data, such as classifying productive and nonproductive periods for equipment. Examples of such commercial software include System Insights VIMANA, TechSolve ShopViz, FORCAM Force, and Memex MERLIN [86, 87]. Gröger and Stach [88] studied the feasibility of a mobile manufacturing dashboard, which allows both shop floor workers and production supervisors to understand performance in real-time.

Another focus here is to better understand complex relationships of factory-level measurements and high-level KPIs through interactive interfaces. Heße and Groh [89] discuss a prototype interface that details facility-related KPIs as movable cards in a hierarchical tree based on their relationships to other KPIs and metrics. Here, environmental sustainability is considered alongside other performance metrics. Similarly, Brundage et al. [90] studied various visual representations of KPIs based on their functional relationships presented in ISO 22400 [67]. A prototype interface is presented that represents each KPI as a small multiples visualization. Each multiple includes a bar chart of related metrics values. Users can modify the low-level metrics to discover various combinations of metric thresholds that meet KPI goals. Users still require expertise or external insights for extending these methods towards sustainability-related data.

4.2.3 Existing challenges and future opportunities

Researchers have emphasized the vital role of visualization in the emergence of smart manufacturing and Industry 4.0 [96]. Furthermore, there is an unmet need for novel methods to incorporate environmental aspects into manufacturing system modelling and simulation [97]. The above factors indicate the potential role of VA tools specifically designed to address the environmental aspects of future manufacturing systems. We discuss possible research directions below.

First and foremost, further contextualization of manufacturing-related information across the lifecycle is heavily needed. Even within manufacturing-specific decision making, e.g. relating production planning to inspection plans and results, significant barriers still remain for integrating and managing knowledge. In spite of the recent progress shown in our review, practical challenges exist. For example, a significant amount of manufacturing information is informally stored in natural language, e.g.

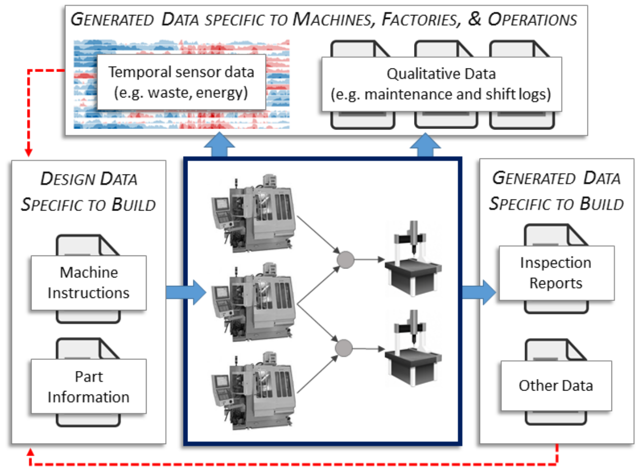

Fig. 6. Overcoming the variety in data formats, contexts, and scales is a challenge for developing VA tools in sustainable manufacturing. A manufacturing environment generates information related both to the operations and build levels in a wide variety of forms, such as natural language maintenance issues and near-continuous data streams [91]. The wide adoption and convergence of manufacturing standards [59, 60, 75, 92–95] present promising opportunities.

quick hand-written notes. Information such as maintenance logs must be formalized within models that specify machines, operators, and status. This will help create data visualizations for intuitive decision-making. Figure 6 summarizes these challenges with an example of a simple manufacturing system (shown in the outlined centered box), including three computer numerical controlled (CNC) milling centers and two coordinate measuring machine (CMM) inspection stations. The data that serves as input to the manufacturing system is related to the specific builds, including machine instructions, e.g. G-code and inspection plans, and part-specific data, such as geometry and material specifications. Here, we show two categories of data generated by the manufacturing system, including (1) data specific to the build, e.g. inspection results, and (2) aggregate data important for operations monitoring, e.g. sensor data and machine maintenance issues. The red dotted lines present opportunities for contextualizing the data generated from manufacturing systems back to design to improve decision-making on environmental performance.

The full realization of smart manufacturing can expedite these solutions [91]. However, to reach such potential, alignment between industrial and academic communities is necessary. A recent survey [98] revealed that, while researchers want to incorporate sustainability metrics like KPIs, industry professionals remain focused on more traditional metrics. An increase in the tracking environmental aspects, such as material waste and energy consumption, can increase the availability of data and knowledge models. On a more positive note, there has been considerable work in the standards community to prepare for such cataloging, such as MTConnect [92–94], recent sustainability efforts in ASTM International [60, 75], and similar efforts in the ISO community [59, 95]. Some work has begun to leverage these or similar technologies to improve the environmental performance of manufacturing systems [99, 100].

4.3 VA Tools for Sust. Distribution/Supply Chains

Supply chains have consistently been studied as an application domain for information visualization. The flow-and-stage nature of supply chains lends itself quite well to graph-based visual representations. For example, Minegishi and Thiel [101] represented supply chain interactions, e.g. cost tradeoffs in production, using a causal loop diagram. Greer [102] incorporated geographic information system (GIS) based information into a multi-level network representation. Hu et al. [103] developed a framework for visually representing geographical attributes of a supply chain using a case study from the transport container industry. TISC-SOFT [104] was presented as a decision-support tool to optimize transportation infrastructure for supply chains. Lin et al. [105] described efforts in representing traditional inventory management information using dynamic interfaces.

Others have focused on creating traditional KPI-based dashboards for supply chain cases. Hesse et al. [106] study effects of various performance-based metrics on inventories. Visually tracking metrics using value stream mapping (VSM) has gained wide adoption for summarizing and monitoring supply chain performance [107]. Khaswala and Irani [108] presented ideas for improving visual layouts of VSM. Others focused on incorporating simulation techniques into traditional VSM [109, 110]. Merging the notion of performance metrics, e.g. risk and resilience, with graph-based visualizations, Basole and Bellamy [111] developed static visual representations of supply chains from the electronics industry to identify hotspots for risks, such as weather disturbances. The work listed above does not explicitly discuss eco-related performance metrics and constraints. Readers interested in developing their own visual representations of supply chains are directed to a dataset compiled by Willems [112] that contains 38 real-world supply chains.

4.3.1 Green supply chains

Here, we present methods and tools that incorporate visual analysis with the goal of designing and monitoring more sustainable supply chains. Many of these efforts have extended on best practices for supply chain visualization and InfoVis, such as including a sustainability-based scoring method for innovation potential [113] and formally modeling carbon footprints [114]. Another example from Faulkner and Badurdeen [115] extended the idea of VSM and built a framework for sustainability-based value stream mapping.

We found little previous work on VA tools for improving the environmental performance of supply chains. One promising effort is Sourcemap, a material-focused tool that allows the user to understand environmental costs per supplier [116]. Sourcemap has an interactive visualization environment and provides an overview of the geographic location of each supply chain using a global map. In the context of SLD, such overlays help in understanding environmental indicators such as carbon footprint resulting from transporting goods/services across geographies. Sourcemap also allows designers to easily identify hotspots for improvement and realize alternative supply chains that are both economically viable as well as more environmentally benign [117].

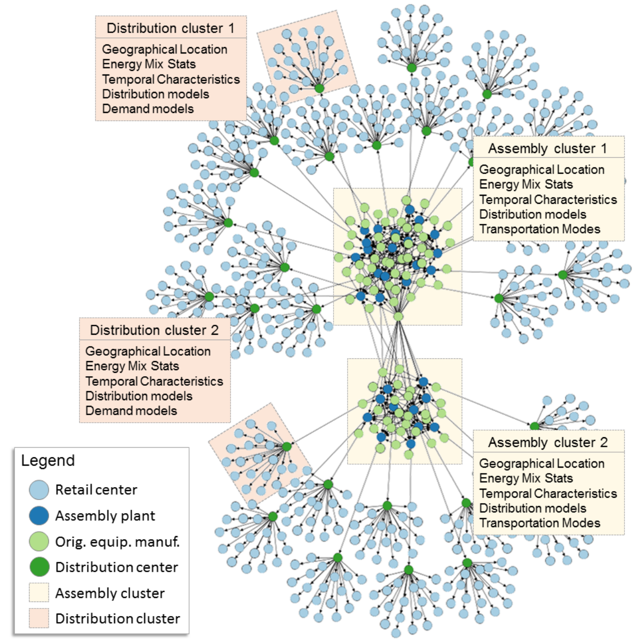

Fig. 7. Supply chains can exhibit unique structures that span multiple geographic regions. This particular example represents the supply chain for farm equipment [112]. As shown, in such systems, distribution sub-networks could have different attributes (i.e energy mix, demand models). Similarly, the characteristics of assembly clusters can depend on it's location. These complexities make it difficult to assess how a change in a supply chain's structure effects it's environmental impact.

Another VA tool, ViSER [118] implements two mutually coordinated panes representing a supply chain tree and a product architecture graph. Users can explore the impact of a change in the supply chain to its product architecture and vice versa. Similar to Sourcemap, ViSER (1) provides updated metrics based on user selection and changes to the network, and (2) shows details-on-demand via a tooltip based on users' interactions. Through a user study with industry experts, ViSER was shown to aid in discovering a variety of redesign opportunities for real-world supply chains [119].

ImpactMap [120] provides a web-based decision support tool that combines information about environmental impact and visualizes data uncertainty levels based on the user's request. Since the primary purpose of ImpactMap is to reflect the uncertainty values and sources of the environmental impact for a particular supplier's location, the most prominent visual variables are codified to pertain to the uncertainty values. The tool also allows the user to adjust the weights assigned to the impact category depending on preference.

4.3.2 Existing challenges and future opportunities

Figure 7 depicts a supply chain representing the distribution of farm equipment [112]. Depending on the product, supply chains exhibit unique structures often spanning across multiple regions, countries, or even continents. Each individual distribution sub-network, shown in red boxes in Fig. 7, could have quite different attributes depending on its location, such as energy mix statistics, temporal attributes, distribution models, and demand models. These characteristics directly relate to the environmental performance of each sub-group. The product procurement and assembly aspects of the supply chain, shown in yellow boxes in Fig. 7 also have their own attributes, important for environmental performance evaluation. Furthermore, changes in one region of a supply chain can affect seemingly unrelated supply chain entities with respect to their environmental performance. All of these challenges are specific to supply chains and must be considered when designing VA tools.

It is difficult to pinpoint the status of VA supply chain tools targeted to improve environmental sustainability in industry. Similar to the manufacturing domain, there are many in-house interfaces built for observing, monitoring, and improving supply chain networks. However, all these tools are not reported to the public. It is our sense that significant challenges remain, based on available reports detailing visualization tools in the industry (e.g. BMW [26]).

Since the visual exploration of supply chains is quite widespread, there is an open need for standardizing visual components of supply chains to promote multi-channel, multi-level, and multi-organizational decision making. Bendoly [121] proposes standard visual variables and plug-and-play components for business processes. Similarly, Beynon-Davies and Lederman [122] attempt to distill theoretical affordances for particular kinds of effective visual variables for tracking the development of products. Case studies in healthcare, clothing manufacturing, and software production are presented by the authors. Such standards for visually representing supply chain components could promote the development and integration of tools that involve multiple stakeholders. However, consensus among interface designers and domain experts is needed through future collaboration.

4.4 VA Tools in the Use Phase

The sustainable use of a product requires recruiting and educating the end user on the impact of their use. The focus of sustainable use has thus been in the realm of human-computer interaction, specifically persuasive computing, ambient awareness, interaction design, as well as pervasive and participatory computing [123]. VA has not made significant inroads to the use phase, mainly due to the challenge of educating the average user in reading abstract visual representations of multidimensional data. Instead, the solution has been on artistic visualizations that use metaphors of natural ecosystems to illustrate the impact of use.

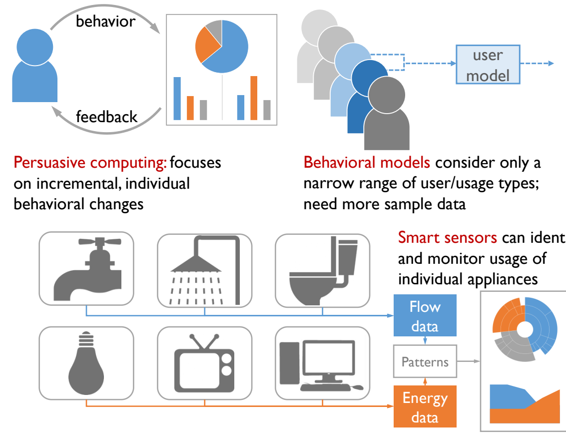

Fig. 8. Challenges in monitoring sustainable behavior in the use phase include limited framing of user behavior in persuasive computing support [131], and the need for user models to consider a wider range of user behaviors [132]. Solutions could lie in the direction of addressing scalability using single, central smart sensors for monitoring resource consumption, coupled with machine learning to identify consumption at the appliance-level [126, 127].

4.4.1 Persuasive computing

Persuasive computing is defined as "interactive technology that changes a persons attitudes or behaviors" [124, p. 225]. Visualization approaches to persuasive computing for the average user often take the form of "ambient awareness". This involves a visualization intended to make users aware of some aspect of their impact on the environment [123]. Examples can be as simple as a lamp whose power cord glows in response to its use, or a room heater that emits light as well as heat to make energy consumption "visible" [125]. Ambient displays can also be more sophisticated. For instance, Ubigreen uses personal ambient displays in the form of mobile phone wallpapers that update with visual metaphors of fruit-bearing trees or an Arctic ecosystem to track and encourage sustainable transportation habits [126].

With the rise in smart products and IoT, it is becoming easier to track user behavior with product performance analytics (Fig. 8). Along with persuasive computing, this has been effectively used through a residence or office building's infrastructure, thus extending its influence from the use of a single product to the use of energy or resources. Examples include using the household water infrastructure to sense activities of water consumption [127], or large-scale visualizations systems for monitoring power generation [128].

4.4.2 Monitoring usage & impact

While artistic visualizations are seen to be more accessible to the average user, Froehlich [129] argues that pragmatic visualizations, though requiring a learning curve for the average user, are better at providing concrete information. Costanza et al. [130] suggest integrating interactive visualizations of users' energy consumption into ubiquitous computing systems. In their field study, they find that when users are allowed to view, modify, and annotate visualizations of their domestic energy consumption, they start seeing energy consumption in terms of activities rather than appliances, and works as a self-motivated persuasive computing system. Perhaps the solution is a combination of both, as seen in examples given by Froehlich [131] where a combination of sensing and persuasive computing is used to provide feedback to users at the individual, household, and social levels, indicating through visualizations and visual metaphors how their actions impact the environment around them.

4.4.3 Existing challenges and future opportunities

Brynjarsdóttir et al. [132] critique persuasive computing support for inducing sustainable behavior as blinkered with a limited framing of user behavior and of sustainability itself. They highlight the methodological issues caused by focusing on incremental as opposed to systemic changes, and on individual behavior rather than societal. They recommend a shift from prescriptive behavior to reflective behavior, which necessitates a shift to participatory design and a broadening of the notion of persuasion from dogma to argument.

It is also critical to inspect computational models used to assess impact. Popoff et al. [133] identify usage eco-drifts: the increased environmental impacts caused by sub-optimal use of products, and argue the case for a model to assess use-phase impact that incorporates a wider range of behaviors. They identify delayed impacts—such as abnormal wear and tear and the environmental cost of repair or replacement—as being critical but hidden factors often not considered in use-phase studies, and suggest a use-phase model that incorporates such impacts. Niedderer et al.'s [134] study of professional stakeholders working on design for behavior change, identified a lack of theoretical understanding in conceptualizing design solutions. This was further linked to lack of availability and consistency in evidence-based examples of prior cases, or a clear connection between theory and practice. Studying and amassing human behavior data is critical: humans are very effective in using their intuition to find optimal solutions to complex problems, as evidenced in eco-racer, a system that incorporates human computation in solving optimization problems [135]. There is potential, therefore, in mining human behavior to identify potential optimal patterns of use for a minimal ecological impact.

4.5 VA Tools for Sustainable End-of-life

Strategies to recover products at end-of-life (EoL) for reuse, repair, remanufacturing, and recycling can help mitigate environmental burdens of products. Identifying optimal strategies for recovery and the impact on profitability is an active concern [136–139]. The increasing ability to gather product lifecycle data is aiding predictive analyses for guiding such decisions [140]. The use of VA tools in EoL can potentially augment human decision making in such scenarios, often characterized by large, complex, and uncertain data.

4.5.1 Disassembly planning

An important aspect of EoL is the ability to plan efficient disassembly for repair, remanufacturing, and recycling. VA tools facilitate designers to visualize computer-aided designs for products and explore disassembly strategies. Previous research has looked at supporting such tasks through immerse virtual environments [141]. Decision-support systems that concurrently visualize life cycle flows and product structure for evaluating alternative end-of-life strategies have also been developed [142]. Another potential application for VA tools is to support the design of modular products. Creating modular products can help ease EoL activities, e.g. disassembly and recycling [143]. Research in SLD has looked at visual representations such as weighted disassembly networks [144], weighted liason graphs [145], and design structure matrices [146] that can be used as the basis for creating future VA tools in EoL. A list of applicable visual representations is reviewed by Gebhardt et al. [147].

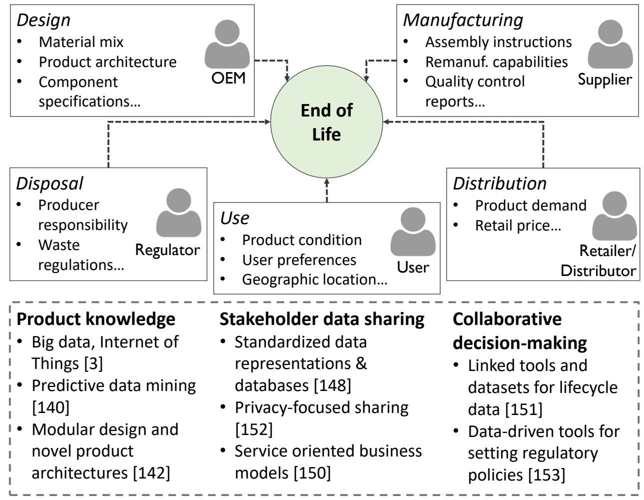

Fig. 9. A key challenge in decision-making for sustainable EoL is the need to gather information from a wide variety of stakeholders across the product lifecycle. Potential research directions towards addressing this challenge are also listed.

4.5.2 Regulatory compliance and waste minimization

Environmental regulations such as the Restriction on Hazardous Substances (RoHS), the Waste Electrical and Electronic Equipment (WEEE), and the End of Life Vehicles (ELV) directive have made it necessary for manufacturers to adopt design strategies for ensuring product compliance and waste minimization. This can be challenging as there are a limited number of approaches in the design phase that support such activities. Bilal et al. [148] conclude that a robust material database with comprehensive support for interactive visualization is required early in the design stage for reducing building construction waste. The same analogy can also be made for minimizing waste from other engineered products. VA tools can help address these issues by presenting such constraints in a linked dashboard that merges design and regulation-related knowledge. One such tool is the Eco Materials Adviser (EMA), available as a plug-in for Autodesk Inventor [149]. EMA links to an extensive database of material properties and offers a co-ordinated multi-view dashboard that helps designers explore interrelationships between carbon footprint, embedded energy and water, material cost, toxicity, and EoL compliance, e.g. RoHS and WEEE.

4.5.3 Existing challenges and future opportunities

Effective decision-making for sustainable EoL requires product-related information generated throughout the lifecycle. As shown in Fig. 9, this necessitates information sharing from stakeholders involved in different lifecycle stages. A lack of information sharing between end-users, third party stakeholders in EoL, and original equipment manufacturers (OEMs), often leads to to poor management of retired products. Fig. 9 also summarizes potential research directions that can help address this challenge.

A specific challenge for creating VA tools in EoL is the ability of OEMs to gather reliable information about the condition of the product as it nears retirement. Stoughton et al. [150] point out that the information in the context of extended producer responsibility (EPR) can be characterized as (1) poorly understood, (2) considerably complex, (3) seemingly unavailable, and (4) reluctantly shared. The development of data-driven information gathering and processing approaches can address this challenge.

Open sharing of collected data can be a significant enabler for sustainable EoL [151] and consequently help the creation of VA tools in EoL. However, the proprietary nature of some of the collected data hinders such collaboration. Approaches for managing confidentiality during collaboration are strongly needed [152]. An additional challenge faced by VA tools in EoL is the need to present and analyze time-series based lifecycle data. For example, VA tools need to present dynamic parameters such as part wear, trends in supply and demand, price fluctuations, and history of ownership in order to better support SLD. Currently, most LCA techniques handle these complex parameters as stochastic processes, often represented by a single percentage value.

A strong potential use case for VA tools is to identify and characterize the interactions among design decisions, recovery strategies, environmental impact, and local regulations. VA tools that can visualize compliance-constrained design spaces and help designers explore the effect of a design change on regulatory considerations can greatly aid design for EoL. Another avenue open to such tools is to aid stakeholders in the design process, analyzing the vast quantities of data that can be gathered by sensors during customer-use of a product. Such tools can be used for understanding the current state of a product and relating product performance to upstream decisions (design for EoL) as well as downstream decisions (co-ordinating product repair or recovery). The rise in technologies such as IoT will fuel this need.

Furthermore, there is a marked shortage in collaboration tools that facilitate knowledge sharing among stakeholders involved in the reverse supply chain [151]. Future VA tools can help address this gap by, formalizing the structure of the knowledge that is to be shared, enabling means for collaboration, and by creating interactive tools for stakeholders to collaboratively plan optimal EoL tasks. Such tools have the potential to reduce the cost of product EoL management and enable more sustainable business practices. Finally, an easily overlooked but significant future opportunity for VA tools is fostering data-driven decision making for setting governmental EoL policies. The use of advanced metrics and LCAs for setting policies is proven to improve the rates of waste recovery and can also aid in reducing waste creation [153]. Data-driven approaches such as sensor-driven data collection of waste streams when coupled with VA tools can help policy makers gain insight into the optimal EoL strategies.

4.6 VA Tools in Life Cycle Assessment

LCA is widely accepted as a means for quantifying and mitigating the environmental burdens resulting from a product or a process [154]. Conducting an LCA requires data about material and energy exchanges from the entire lifecycle. Such information is vast, uncertain, and therefore complex [155]. Furthermore, since LCA is built without an explicit link to decision-making, translating the results from LCA to avenues for redesign is often challenging [156]. Thus, VA tools can play an important role in helping practitioners and designers gain deeper insights into the process and the outcomes of an LCA.

4.6.1 Inventory analysis and results exploration

One of the first interactive VA tools for exploring LCA results was VisEIO-LCA [157]. The tool aids LCA experts explore results from economic input-output LCAs (EIO-LCA) [158]. VisEIO-LCA was informed by conducting a needs analysis to understand the kind and frequency of tasks performed by EIO-LCA users. It consists of a multi-view interface that visualizes EIO-LCA results using charts, matrix plots, scatter plots, and geographical map visualizations. Norris & Yost [159] mention that, (1) publicly available transparent life cycle inventory (LCI) data, and (2) the use of interactive software for LCAs, are necessary for promoting sustainable building design. To this end, the authors created Life Cycle Explorer (LCE)–a tool for promoting LCA transparency through interactive exploration. To help LCA practitioners understand dominant factors in comparative LCAs, LCE provides means for creating comparative scenarios and conducting probabilistic uncertainty analysis.

Apart from these efforts, researchers have looked at developing tools and methods relevant to VA tools in LCA, including (1) novel glyph-based visual representations for LCA results [155], (2) the addition of interactivity to LCA results visualizations [160], (3) an interface for neighborhood-level visualization of household carbon footprint [161], (4) a visual interface for environmental load estimation and labeling [162], (5) an LCA-based toolbox incorporating data visualizations to aid pollution prevention and waste minimization [163], (6) a visual exploration tool for the QUEST sustainability model [164], and (7) relating LCA results with design using dynamic interfaces [42].

4.6.2 Web-Enabled tools

The increasing ease of creating dynamic websites and connecting them to large-scale databases has helped the creation of web-based VA tools in LCA. A significant advantage of such tools is that they are easier to disseminate using the Internet. Two such efforts that enable web-based visual exploration of LCA results are Antelope [165] and Brightway2 [166]. Antelope is a web-based service for publish-

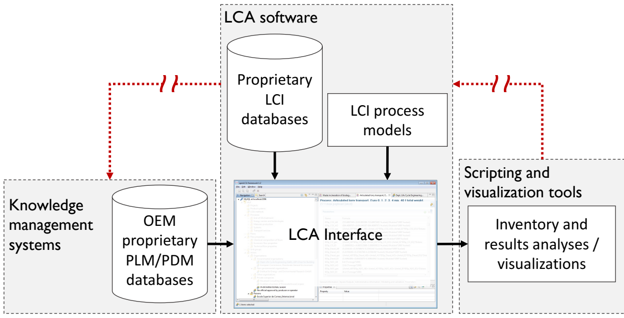

Fig. 10. Current LCA software and tools for analyzing/visualizing LCA results are not sufficiently integrated with enterprise knowledge management systems. Consequently, there is a lack of information flow back to PLM/PDM databases; denoted by the break in the dotted red arrows in the Figure. Addressing this challenge could significantly aid sustainability-focused decision making throughout the product lifecycle by helping organizations archive and make better use of previous LCA studies. Potential research directions towards achieving better integration, include open-source software and LCI databases [168–170], non-proprietary data sharing standards [171], and cloud-based and web-based LCA platforms [165–167].

ing LCA models and results. An implementation of Antelope that visualizes environmental impacts of recycling motor oil is available online[1]. This implementation allows LCA practitioners to interactively explore the inventory model and also compare LCI analysis results for different scenarios. Brightway2 is an open source framework for LCA that uses the Python programming language[2]. This allows LCA practitioners to use graphing libraries, e.g. Matplotlib[3] and D3.js[4], to create interactive visual representations of LCA data. While Brightway2 is not a VA tool for exploring LCA results, it creates the necessary software framework for researchers and practitioners to build such tools. A related commercial effort is SimaPro Share & Collect [167]: a web-based platform that allows LCA practitioners to upload their LCA models, perform scenario analysis for project managers, and collect LCA data through online surveys. SimaPro Share & Collect helps users gather information from various stakeholders and perform what-if analyses. To facilitate exploration, interactive visual representations are linked to datasets and scenarios.

4.6.3 Existing challenges and future opportunities

Current LCA tools are not well integrated into knowledge management systems. As LCAs do not capture interdependencies between product architecture and process requirements across the lifecycle, it is challenging to relate this information to data in PLM/PDM databases [172]. Consequently, it is challenging to create VA tools in LCA facilitating sustainable design by concomitant exploration of design and sustainability data. Figure 10 illustrates this challenge, detailing the separation of OEM knowledge management systems, LCA software, and scripting or visualization tools used for analyzing LCA results. The proprietary nature of LCIs, data formats, and LCA tools creates hurdles for interfacing VA tools, LCA software, and PLM/PDM databases. Efforts to create open source LCA tools [166, 168], public LCIs [169, 170], non-proprietary data exchange standards [171], and guidelines for exchanging information models, may reduce this barrier.

The lack of data interoperability between environmental assessment tools (such as LCAs) and PDM/PLM repositories creates challenges in relating LCA results to lifecycle design variables. As a result, creating VA tools that overlay LCA results onto part attributes is not trivial. This is further complicated by the fact that specific visual representations are used in different lifecycle stages. As an example, supply chains are commonly visualized using graph networks, early design often uses function diagrams, and 3D models or detailed drawings are commonly used in the manufacturing stage. Therefore, VA tools that facilitate lifecycle decision-making using LCA results, need to visualize specific product attributes, using specific visualization schemes, based on the lifecycle stage. In response to these challenges, researchers are exploring visualization taxonomies and techniques in contexts such as production simulation [79], sustainable building design [37], and sustainability indicators [173]. Further research is needed to develop holistic visualization frameworks that integrate visual representations for LCA results and product lifecycle data.

Another challenge is the prevalence of significant uncertainties resulting from poor data quality, invalid or non-transparent assumptions, and lack of site-specific inventories [174]. VA tools in LCA need to convey these uncertainties in a transparent and easy-to-understand manner for effective decision-making. Glyph-based techniques for conveying uncertainties in LCA results have been proposed [175]. However, understanding the efficacy and scalability of such visualizations for LCA results remains an open question. To overcome the challenges described above, the creation of future tools should consider supporting the following activities.
1) *LCA Data Exploration:* Most data for performing LCAs is manually collected [176]. Data-driven methods for gathering and processing lifecycle data can help industries transition to a more automated data management approach. With this move, the need for gaining insights about data quality becomes an important concern for validating LCA reliability. Creating VA tools for exploratory data analysis can help LCA experts gain insights into the data and complement the use of automated approaches for confirmatory analysis.
2) *LCA Model Structure Exploration:* The re-purposing and reproducibility of assessment models is now a research focus for the LCA community [177]. A primary driver of this effort is separating data and their sources from the general model representation. In manufacturing, similar efforts are on-going to formally standardize sustainability models for manufacturing process, to improve LCA unit process accuracy and to make them more amenable to engineering analyses, e.g. discrete event simulation and optimization [178]. There is a significant opportunity for research to address the

[1] www.uo-lca.github.io/
[2] www.python.org/psf/
[3] www.matplotlib.org
[4] www.d3js.org

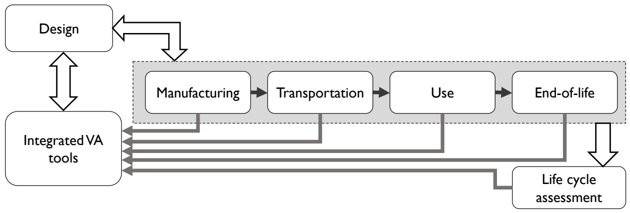

Fig. 11. Product lifecycle data from downstream stages and results from environmental assessments, e.g. LCAs, need to be projected back through integrated VA tools for holistic decision-making in SLD. Such tools enable designers to perform data-driven analyses of the implications of design changes on environmental performance.

role of VA tools in promoting transparency and standardization of LCA model structures through exploration-focused interfaces that support insight generation.

3) *Stakeholder Collaboration:* LCA results are too complex for designers not well-versed with environmental assessment [179]. Often, this leads to an over simplification of results that can obscure actual hotspots. While previous work in SLD has looked at design-focused tools to address this challenge [180, 181], it has been argued that LCAs are most effective when conducted by an environmental actor external to the design process [182]. In both cases, there is a strong need to support collaboration, either among designers or between designers and LCA experts, to facilitate better decision-making. Current commercial LCA tools are limited in that they do not scale well to a group of connected users and are independent of existing enterprise information systems [176]. While extensions such as SimaPro Share & Collect start to address stakeholder collaboration, future VA tools in LCA can look at bridging this gap by acting as an intermediate layer between PLM and LCA to facilitate the collaborative, simultaneous exploration of data and models.

5 FUTURE RESEARCH DIRECTIONS

In Section 4, we presented domain-specific challenges stepping through various stages in the product lifecycle. Significant domain-specific challenges in each lifecycle stage were illustrated in Figs. 5-10. In this section, we summarize and contextualize these challenges to position research directions for improving VA tools relevant to SLD.

5.1 Domain-specific challenges

To fully realize integrated VA tools for SLD, shown in Fig. 11, domain-specific challenges in data collection, processing, and visualization must be overcome first. A significant issue in the design stage is mapping environmental performance to design constraints and parameters, as shown in Fig. 5. The emergence of Industry 4.0 presents a potential answer towards this challenge through the use of data-driven approaches to automatically gather and extract relationships between design variables. For manufacturing, merging various data representations from different perspectives, e.g. machine instructions and generated sensor data, is still an open problem, as shown in Fig. 6. More efforts towards developing standardized data representation and exchange formats, e.g. MTConnect [92], ASTM E3012-16 [60], ISO1469-1:2003 [95]) are needed. The complexity of supply chains and unique characteristics of their subsystems present barriers for understanding environmental performance, (see Fig. 7). Advances in technologies such as IoT can help fill data gaps in complex supply chains. Data-driven approaches for generating meaningful insights from heterogeneous, multidimensional networks can aid in designing green supply chains. With regards to the use-phase, developing robust behavior models that capture a variety of usage patterns remains a problem, as shown in Fig. 8. A combination of data-centric approaches for pattern detection (such as machine learning), and crowdsourcing studies to understand user behavior, can potentially address some of these issues. Data gathering from multiple stakeholders complicates sustainable EoL practices. Potential research directions to tackle this challenge are shown in Fig. 9. Lastly, challenges in LCA relate to the lack of interoperability between LCA software and supporting tools such as PLM databases and visualization scripts, as shown in Fig. 10. The emergence of web-based LCA platforms, standardized data representations, and open source inventory models/software can help bridge this gap.

The issues discussed above relate to challenges in data gathering and integration. Overcoming these challenges is essential for creating effective VA tools for SLD. However, only solving such issues will not necessarily ensure success. VA-specific challenges in tool design and dissemination pose additional hurdles.

5.2 VA-specific challenges

Our review shows the relatively limited number of VA tools across various stages in the lifecycle, as seen in Table 2. VA-focused challenges identified here can be summarized as follows, (1) procuring data to develop VA tools for SLD, (2) distilling design patterns (or a set of best practices) of existing successes to inform the design of such tools, (3) formally characterizing appropriate evaluation protocols to judge the efficacy and utility of these tools, and (4) disseminating these tools in real industrial settings.

The latter of the listed issues should not be understated. Practical challenges exist while deploying (even well designed) VA tools into an organization. After a 3.5-year collaboration with a major automobile manufacture, Sedlmair et al. [26] summarized a holistic set of encountered barriers. Some issues are similar to the challenges identified in this paper, e.g. tool/data integration, evaluation protocols, and data collection. However, the authors also highlight "political and organizational issues" that "may require highly collaborative synchronization efforts and may become long and exhausting" [26]. Such problems also arise when disseminating and implementing data format and integration standards. As a result, continual education with convincing demonstrations of use cases is essential to garner industry buy-in.

5.3 Future research directions

Based on the challenges and discussion presented above, we list possible research directions. These directions encompass research on lifecycle data modeling, computer-

Table 2. Summary of references related to each lifecycle stage. References (second column) map to works cited in that section. The third column specifically highlights visual analytics tools that explicitly mention sustainability-related improvements and their supported activities.

LC Stage	References	Visual Analytics Tools for Sustainability with Supported Activities
Design [Sec 4.1]	[8, 12, 30–56, 58–65, 180, 181]	shapeSift [40]: explore 3D part repositories for eco-conscious decision-making TRIZ + LCA [41]: transforms LCA impacts into potential eco-improvements Uchil et al. [42]: relates LCA results with design Greenberg et al. [43]: predicts energy use and emissions for buildings Others [48–54]: supports building design & urban planning for sustainability
Manufacturing [Sec 4.2]	[59, 60, 66–100]	Herrmann et al. [81]: tracks energy-based simulation as user explores sets of controls Rebouillat et al. [82]: composes set of process models to explore sets of controls SIMTER + Gantt [84]: explores simulation environment by interacting with Gantt chart Wörner and Ertl [85]: explores factory simulation through a coordinated dashboard
Supply Chain [Sec 4.3]	[26, 101–122, 183]	Sourcemap [117]: presents geo-location of suppliers in a web-based tool ViSER [119]: shows coordination between supply chain and product architecture ImpactMap [120]: aids supply chain design while incorporating uncertainty
Use-phase [Sec 4.4]	[123–135, 184, 185]	BuildingOS [185]: supports energy monitoring through an interactive dashboard
End-of-life [Sec 4.5]	[136–153]	Berg et al. [141]: supports disassembly planning through a virtual environment Fukushige et al. [142]: visualizes LC flows & product structure to compare EoL options Eco Materials Adviser [149]: provides dashboard to help comply with waste regulations
Life cycle assessment [Sec 4.6]	[37, 42, 44, 79, 154–182]	VisEIO-LCA [157]: aids in exploring LCA results from EIO-LCA Life Cycle Explorer [159]: creates different scenarios and conducts uncertainty analysis Antelope [165]: publishes LCA models and presents results Brightway2 [166]: provides necessary software framework for building VA tools SimaPro Share & Collect [167]: provides platform for sharing & re-using LCA models

supported interfaces, and sustainable lifecycle design—the domains underlying VA tools for SLD (see Fig. 1).

To expedite development of VA tools for SLD, there is a need to reduce the barrier for creating research prototypes and testing them with real-world data. This requires publicly available datasets, vetted by domain experts and well publicized to the SLD community. A few existing data sources include Purdue's Shape Benchmark [186], the Design Repository[5] [187], the NIST Smart Manufacturing Systems Test Bed[6], open LCI databases [169, 170, 188], and 38 real-world supply chains [112]. More datasets from reliable sources will improve re-usability and extendibility of VA tools.

Another vital research direction is the need for interoperability between VA tools in SLD. Technologies such as the semantic web, are a promising and emerging field, and can potentially trace linkages across different lifecycle stages [55, 189]. In this regard, one promising effort is the Industrial Ontology Foundry (IOF), a collaboration in its infancy aiming to construct standardized ontologies for product lifecycle data. These openly available sets of ontologies will abide by the Basic Formal Ontology (BFO) [190]. The BFO has been widely accepted in the biology community for (1) advancing the sharing and dissemination of medical taxonomies and (2) providing a common platform for conducing advanced bio-informatics [191]. The expectations of the IOF is to enable similar opportunities for the engineering community. Interested readers can refer to initial work from Furini et al. [192] that provides a BFO-based ontology for functionally graded materials. Structured taxonomic representations, such as those presented by Kumaraguru et al. [193], also expedite the prototyping of visual representations, as shown by Li and Bernstein [194]. These efforts will also benefit from the development of a minimum information concept for lifecycle data in the context of SLD which can enable better data verification and analyses across the community [195].

There is also a need for research focusing on the development of integrated VA tools for SLD. The rise in data generated in each life cycle stage and the necessity for synthesizing design insight from these data, motivates the creation of integrated VA tools. As shown in Fig. 11, such tools must be capable of merging lifecycle data with results from environmental assessments helping designers extract causal relationships. Simultaneously, such tools should also help designers assess the impact of a design change on downstream lifecycle stages. To fully realize this vision, harmonization of standards on related data representations as well as monitoring and assessment techniques mentioned throughout this paper [56–60, 67, 75, 92–95] is strongly recommended. To ensure that future work will be more sharable, reproducible, and applicable across domains, research and effective collaboration is needed to overcome these significant challenges. Highlighting some early successes, Narayanan et al. [196] developed a visual query system for the landscape of product engineering standards. Another example illustrates the use of existing out-of-the-box VA tools [197] for presenting results from analyzing standard design representations[7].

Finally, linking theories about the design process to theories within the human-computer interaction community

[5] http://design.engr.oregonstate.edu/repo
[6] http://smstestbed.nist.gov
[7] https://pages.nist.gov/CAD-PMI-Testing/results.html

might help create more contextualized tools offering greater utility for decision-makers. Providing guidelines for environmental informatics and sustainability informatics including their link to visualization technologies [198, 199] will help drive SLD into more actionable product planning.

6 CONCLUSIONS

Sustainable lifecycle design (SLD) has seen significant growth as a research field over the past few decades. Researchers, educators, and industry practitioners, have been successful in making SLD one of the focal areas in engineering. Even so, several barriers exist towards the goal of holistically integrating sustainability into engineering theory and practice. Our review points to one such important barrier—the lack of approaches for gathering and synthesizing information flows from downstream lifecycle stages in a manner that is useful for design. The rapid rise in technologies for data collection will partly address this challenge. However, the opportunity to advance SLD through data-rich tools is dependent on the ability to translate big data into big insight. Doing so requires novel SLD tools that can combine automated, data-driven approaches for life cycle data collection and analysis with user-driven approaches that enable domain experts to use their own expertise and intuition in generating novel insights. A promising approach for combining the two is by creating visual analytics (VA) tools in SLD that facilitate analytical reasoning using interactive visual interfaces.

In this paper, we review previous research that has created VA tools in the context of SLD. We also highlight existing challenges and future opportunities for such tools in different lifecycle stages—design, manufacturing, distribution and supply chain, use-phase, end-of-life as well as life cycle assessment. While the number of VA tools in SLD is relatively small, researchers are increasingly looking into this topic. Our review points out that VA tools can potentially address several existing challenges in SLD and that significant future opportunities still exist. The growing use of VA tools in related applications such as design of complex systems, environmental informatics, and public policy, strengthens the case for exploring their use in SLD. Key contributions of our paper include: (1) motivating the need for VA tools in SLD, (2) illustrating the scope of VA tools in SLD (see Fig. 1), and (3) outlining a possible architecture for future integrated VA tools in SLD. We hope that this work will aid the SLD research community in multiple ways. Our review of previous VA tools will help researchers identify relevant works and learn from the successes and limitations of these approaches. We hope that the identified challenges for creating such tools and the future directions that we have suggested will help guide researchers interested in exploring this research area.

Lastly, we also hope that our work will serve as an open call for visualization and human computer interaction researchers to collaborate with the SLD community. Life cycle information in the context of SLD is vast, uncertain, complex, multi-modal, and sourced from heterogeneous data sources. At the same time, it has open problems that we believe can be addressed through VA-like approaches. To conclude, the summation of these two areas–VA and SLD—has the potential to create a unique research niche that can make new in-roads into the grand challenge of achieving sustainable development.

DISCLAIMER

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