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ADAPTING CONSUMER PRODUCT DESIGN TO THE CIRCULAR ECONOMY

Vincenzo Ferrero, Buddhika Hapuwatte, KC Morris
Systems Integration Division
National Institute of Standards and Technology
Gaithersburg, Maryland, 20899
Email: Vincenzo.Ferrero@nist.gov

ABSTRACT

Transition to a Circular Economy (CE) will be facilitated by information transfer between life cycle stages, and, particularly, the transition can be accelerated at the product design stage where the decisions have impact throughout the life cycle. Product design, which is often manual, subjective, and speculative, can be enhanced by data transfer from other stages of product, manufacturing, material, and supply chain life cycles. Mutually, the CE system can benefit from design systems that are real-time, designer-in-the-loop, and dynamic with respect to life cycle information streams. Five identified challenges toward adapting product design to the CE are

1. *Consolidation and identification of DfX areas critical to the CE*
2. *Realization of a digital thread to the design activities*
3. *Incorporation of designer-in-the-loop and AI design agents*
4. *Introduction of CE data-driven design methods*
5. *Development of CE design standards*

A literature review in each challenge area identifies future research areas. Finally, a preliminary circular product design convergence model is introduced to illustrate a CE consumer product design system that addresses the challenges and research opportunities. The work contributes a framework within which product design can be improved to aid in the realization of Design-for-the-CE. The circular product design convergence model can be a framework for exploring standards-driven and validated solutions to these challenges.

Keywords: Circular Economy, Product Design Systems, Digital Thread, Digital Twins, Sustainable Manufacturing

1 INTRODUCTION

Dynamic and fundamental changes to the manufacturing economy are resulting from a movement to a circular economic model from the dominant classical linear economic system [1]. The current manufacturing economic system is defined by a cradle-to-grave perspective where the scope of the economic system begins with material acquisition from a black box–representing economic systems that produce materials– and ends with the disposal of the product back into a black box–representing various end-of-life economic systems. In the system, the consumed products and by-products are no longer tracked in the original economic scope become "waste", where *original economic scope* is defined as the initial single life cycle of the product and ends with the cessation of the original enterprise's purview over the product. In contrast, the circular economy (CE) focuses on triple bottom line sustainability improvements and maximizing the time resources effectively stay within the economy regardless of the original economic scope. Through analysis of 114 definitions of a CE, Kirchherr et al. [2] presents the formalized CE definition as

> A Circular Economy is an economic system that replaces the 'end-of-life' concept with reducing, alternatively reusing, recycling and recovering materials in

production/distribution and consumption processes. It operates at the micro level (products, companies, consumers), meso level (eco-industrial parks) and macro level (city, region, nation and beyond), with the aim to accomplish sustainable development, thus simultaneously creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations. It is enabled by novel business models and responsible consumers.

In the CE, waste is mitigated, while by-products and disposed of products are used in another economic scope. Moreover, while this does occur to some capacity in current economic systems, such as through secondary markets, the implications of a system of connected product life cycles is not widely understood. In a CE, we strive to remove the black boxes of the current economic system for use during the design process and fully realize the complex system of systems that can facilitate the maximized potential of resources remaining in the economy.

A study, published by the Club of Rome [3], investigating seven European country economies, suggests that the adoption of a CE system can reduce greenhouse gas emissions by 70% while increasing the labor force by 4%. This study is corroborated by the Ellen MacArthur Foundation [4]. The Ellen MacArthur Foundation report states that a transition to the CE could reduce greenhouse gas emissions by 2030 compared to the current global economic system. A decrease in resource consumption can lead to 1.4-2.8 million new jobs in the European Union. Although many economic aspects, including business strategies, improved resource recovery, and consumption reduction, are hallmarks of a CE, we assert that realizing these economic aspects begins with CE-focused product design.

In the context of CE-based product design, the objective is to maximize value at each part of the product life cycle [5, 6]. In a CE, product design presents opportunities for innovation by considering multiple life cycles and end-of-life planning that can lead to regenerative resource flow [7–9]. However, for product design, circularity is not just measured by classical sustainability indicators such as material reduction or resource recapturing [10]. In product design, circularity success and measurement is partially a function of data sustainability, information transformation, reuse, and recapture [11–14]. Product design in a CE relies on life cycle digitization and data transfer back toward product design activities. Realizing life cycle data transfer back to design activities requires solving the data-disparity challenges that inhibit robust data-driven product design systems.

Currently, in product design, information transfer to the design process occurs through management chains, company culture, market research, and other shallow data sources that hinders the ability for product designs to adapt automatically to changing conditions. We can improve weak data sources by expanding information transfer to the design process, involving product design in all parts of the product life cycle, introducing human-in-the-loop AI agents, and improving response times toward stimulus that cause design changes. Needed advancement toward an adaptive design cycle for a CE includes identifying *Design-for-X* areas critical to the CE, where X can be disassembly, end-of-life, and sustainable product development. Beyond a *DfX* focus, the digital thread and life cycle digitization can be expanded to provide direct data streams from all product life cycle areas filling the informatics gap. Finally, inclusion of temporal data streams to design through digital twins can help move design activities away from speculation-based approaches and toward a reactive time-dynamic data-driven design approach [15].

In this paper, we review a CE model and the classical design approach to provide the context of both systems. Using this context, we postulate five challenges to successfully applying product design to the CE system:

1. Consolidation and identification of *DfX* areas critical to CE
2. Realization of a digital thread to the design activities
3. Designer-in-the-loop and AI design agents
4. CE data-driven design methods
5. CE design standards

For each challenge a literature review provides the context of what has been done and has yet to be done. The contribution of this work is to provide a foundation for defining multiple research challenges that the academic community can take up. Furthermore, we introduce a model for enhancing the classical design approach toward adaption in the CE. Through a literature review of modern developments in product design toward Sustainable Product Development (SPD) and realizing the CE, we formulate a data-enhanced design approach to improve the success and applicability to product design within a CE where designer-in-the-loop is critical. Through this paper, we invite collaboration to solve the proposed challenges to help materialize topics discussed here.

2 A CIRCULAR ECONOMY MODEL

Before understanding how classical product design can be adopted for success in a CE economy, we must first understand the circular economy. As previously mentioned, a *Circular Economy* is defined as the total elimination of "waste" within an economic system [16]. That is, manufacturing by-products and remains, including used products, are continuously re-introduced into the manufacturing cycle. Strategies advantageous to the CE include reducing resource sinks, reusing manufacturing by-products and products, disassembly and re-manufacturing of products, and reclaiming and recycling discards. Materials with limited recycling potential should enter and remain in the economy for long periods and slow material loops; examples of this include carpets, pipes, and structures, which often have multi-decade lifespans [17, 18]. To better provide an understanding of

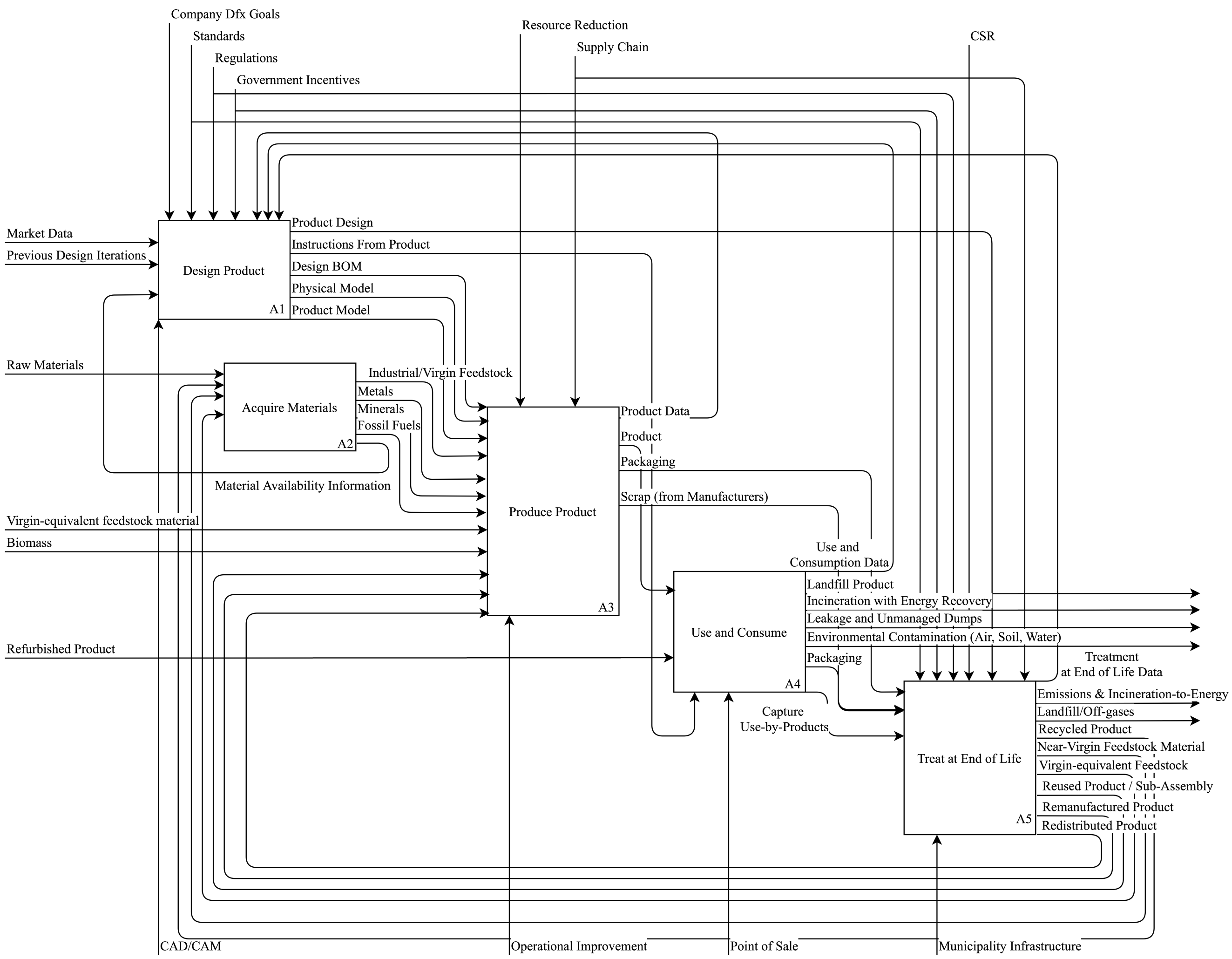

FIGURE 1: A manufacturing-based *Circular Economy* IDEF∅ A0 top-level model.

a manufacturing CE, we have provided a CE model created using IDEF0, shown in Figure 1.

IDEF0 is a modeling methodology that provides multiple levels of abstraction and describes the interactions of a system and functions within the systems [19, 20]. Figure 2 provides an overview of the structure of an IDEF0 activity. Inputs are the flows intended to be modified by the activity or function. Outputs are the resultant flows from the function. Controls are coordination criteria that are used to direct the activity. Finally, mechanisms are tools and methods that can facilitate the activity. Activities are arranged in an IDEF0 diagram in relation to other activities, as is done in Figure 1.

The CE model is defined by the same five major life cycle activities found in current manufacturing economic models. These are Design Product, Acquire Materials, Produce Product, Use and Consume, and Treat at End-of-Life (EoL). Differences

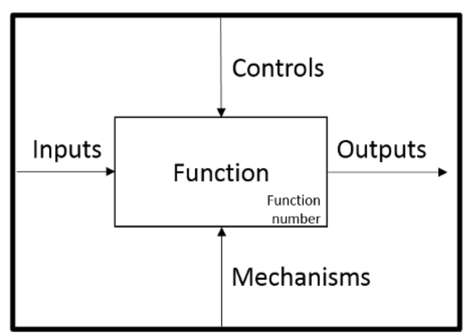

FIGURE 2: IDEF∅ format guide

arise through feedback loops introduced to ensure that resources stay within the economy for more extended periods of time. For instance, in Figure 1, activity A5–Treat at End of Life has enhanced focus on bringing products back to A2–Acquire Materials and A3–Produce product. Common applications of a circular economic system help facilitate the realization of these feedback loops and diminish products entering landfills. As partially shown in Figure 1 and beyond, this may include expanding recovery and recycling systems, improving industrial symbiosis, setting up material marketplaces, and advancing company-specific product recovery [21–23]. However, considering the classical product design process, these efforts may not directly impact consumer product design. To adapt consumer product design to the CE, we need to introduce a circular economy of data and information. Thus the realization of a CE of information is to realize the movement from abundant but disparate data systems, to interoperable data systems that focus on interdependence of human and artificial intelligence. Product design in the CE should allow the transfer of informatics from all areas of the product life cycle back to human and AI designers, fully realizing the idea of designer-in-the-loop where the designer is involved beyond the classical design process, or in the case of the presented IDEF0 model (Figure 1), beyond activity 1.

3 THE CLASSICAL DESIGN APPROACH

The classical consumer product design approach is outlined in Figure 3. As outlined in the book, *The Design Process* [24], product design begins with problem identification, where the designer determines current gaps in the market. This problem identification often comes from beyond the design team and is influenced by company goals, government regulations, modernization, and market share upkeep [25, 26]. Following problem identification is analyzing stakeholders and determining customer needs to develop consumer profiles. These activities are governed by company and market culture. Engineering specifications are then defined to quantify how customer needs are met. Then, through an iterative approach, product concepts are generated, evaluated, and finalized. Upon successful prototyping and company acceptance the product design enters production.

Throughout the classical design process, several design tools are used. These tools include focus groups, house of quality, morphological matrices, Pugh charts, internal product criteria measurements, and CAD programs. However, these tools are not knowledge or data-rich and require expertise and cognitive approaches [27–29]. They are limited by the capabilities of the designer or design team. In this capacity, current efforts to supplement the data and dearth of information within consumer product design include design automation, multidisciplinary design teams, and internal data capture and knowledge extraction [30–32]. However, consumer product design largely remains a 'lessons learned' activity that is supplied data from sources that are often speculative, product review-based, enterprise internal, and narrow in scope. Although these sources of data, combined with expert design teams, prove paramount to successful product design, as we move from current economic systems to the CE, introducing the designer into the product life cycle loop is beneficial. In other words, information circularity is of the utmost importance to support the dynamic systems of systems that are critical to CE.

Specific to an CE system, designers need to take real-time information and make dynamic decisions based on uncertain material streams, product use locality, secondary markets, industrial symbiosis partnerships, derivative product life cycles, and changing regulatory requirements. It is crucial that the designer has insight into the entire circular economic system including current, previous, and derivative product life cycles. Data-driven approaches are necessary to supplement the lack of comprehensive life cycle expertise. The scenarios explained can be defined by a set of CE transitional challenges. The following section highlights these challenges of information exchange, knowledge extraction, temporal design tools paired with digital twins, and artificial intelligence design agents that can help manage design complexity for the realization of CE systems.

4 TRANSITIONAL CHALLENGES IN PRODUCT DESIGN TOWARD A CE

The five challenges explored in this section require solutions to adapt consumer product design to the CE system. These challenges are not the only challenges faced in achieving successfully product design systems in the CE. However, these challenges represent immediately attainable research areas by leveraging data and progress from Industry 4.0. Here we introduce each challenge, provide a literature review of current research, and highlight opportunities for future contribution.

4.1 CHALLENGE 1: CONSOLIDATION AND IDENTIFICATION OF DfX IDEAS CRITICAL TO THE CE

Design-for-X is defined by special consideration of specific objectives as they apply to new product development (NPD) [33]. Modern *DfX* areas include, but are not limited to, design for manufacturing, sustainable product design, design for assembly and disassembly, and design for obsolescence resilience [34–36]. In consumer product design, *DfX* has increased design complexity, and motivated specialized designer expertise, along with the advent of multidisciplinary design teams [37, 38]. Today, design teams can include Life Cycle Analysis (LCA) practitioners, psychologists, data scientists, and process engineers. Multidisciplinary design teams subsidize knowledge needed for innovation and successful market introduction of new products. As such large enterprises have facilitated mechanisms to curate large design teams and robust design processes [39, 40]. These design teams and robust internal design systems can easily be directed to respond to in response to the CE. In contrast, small and medium

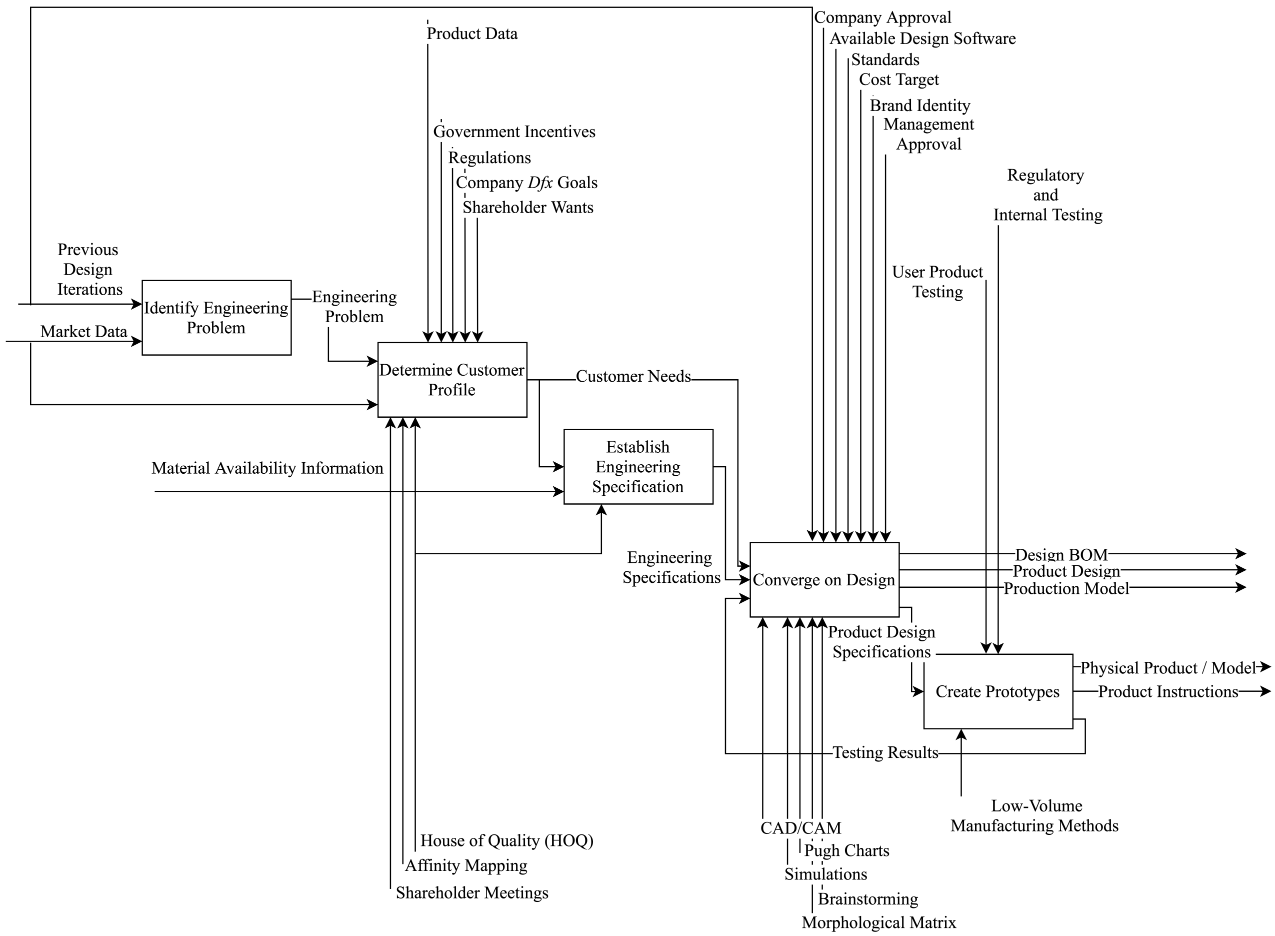

FIGURE 3: A Consumer Product (high-volume/low-mix) Design IDEF∅ model.

enterprises with single design engineers may struggle to keep up with increasingly complex design requirements found in the CE. However, when compared to large enterprise hierarchical structures, these smaller enterprises are likely equipped to quickly implement dynamic changes in response to CE stimulus. Regardless, small-to-large global product producing enterprises can benefit from research-based distillation and ranking of *DfX* areas that are critical toward the realization of the CE.

An early example of literature *DfX* toward a CE points toward design topics including slowing and closing resources loops [41]. Design for slowing resource loops encompasses design for long-life products and design for product extension. Design for closing resource loops includes design for disassembly and reassembly, design for the technological cycle, and design for a biological cycle. Metre and Cooper presented these coined *DfX* terms as a conceptional framework for circular product design [8]. In the focus of metallurgical infrastructure and product design, design for recyclability is listed as a CE challenge [42].

CE builds on the principles of sustainable manufacturing, particularly design for resource efficiency. Earlier work at the National Institute of Standards and Technology explored how insights from manufacturing production could be used during product design to increase production efficiencies [43, 44].The work emphasizes the use of sharing information from production back into design through simulations and information flows, thereby enabling more robust simulations of production systems to inform design decision making. The work resulted in a series of standards from ASTM E60 Committee on Sustainable Manufacturing for digitally modeling manufacturing processes for environmental improvement [45].

Recently, Sassanelli et al. [46] explored the understanding of *DfX* in the context of contribution toward circular design solutions. They claim that circularity can only be addressed by consideration of multiple *DfX* areas concurrently. Through this literature *DfX* for the CE separated into five classes. The classes and related *DfX* areas are:

1. Supply Chain: Design for Supply Chain

2. Resource/energy efficiency: Design for Resource Efficiency and Conservation, Design for Multiple Users, Design for Product Sharing
3. Reliability: Design for Slowing, Design for Maintenance, Design for Product-life Extension, Design for Serviceability
4. Multiple Life Cycle: Design for multiple life cycles, Design for Disassembly and Reassembly, Design for Remanufacturing, Design for recovery, Design for recycling, Design for End-of-Life, Design for Standardization
5. Sustainability: Design for Sustainability, Design for Environment, Design for Social Responsibility

Through this literature review of CE *DfX* areas, and specifically through Sassanelli et al.'s work, we begin to establish a list of current design areas essential to the CE. However, it is yet to be determined *how* important these *DfX* areas are toward the CE. In addition, a better understanding of the interoperability of these *DfX* areas is also needed. Lastly, novel or underdeveloped *DfX* areas may be crucial to the CE as well. As an example, design for industrial symbiosis, design for personalization, design for social responsibility, and design for supply chain uncertainty can be explored as a design focus. Upon meeting the specific challenges discussed, we can adequately define *Design for a Circular Economy*.

4.2 CHALLENGE 2: REALIZATION OF A DIGITAL THREAD TO THE DESIGN ACTIVITIES

The digital thread is defined by the data connections created to improve the interoperability of disparate product and production life cycles areas [47]. The digital thread has been used to connect standards throughout manufacturing. For example, the standard representation of machine input codes such as NC code and G code have been mapped to the machine execution language standard MT Connect [48]. The creation of this digital thread allows for data of manufacturing errors to be translated and transferred upstream and mitigated during production planning.

Toward product design, Singh et al. [47] assert the possibility to leverage the digital thread to help create compelling designs for next-generation products. However, research exploring conceptual product design in the context of data from other areas of the product life cycle remains underrepresented [49]. Again, this points to the lack of data streamed back to product design processes, leaving these processes manual and based on speculation. To answer the identified lack of a product design digital thread, a digital twin and digital thread framework have been introduced to improve the efficiency of product data management that can aid in data-driven design approaches [50]. However, there is still a need to expand on current literature by applying digital thread and digital twin representation connecting product design to life cycle data instead of generic product data. For example, End-of-Life data concerning recycled, upcycled, and recaptured materials can provoke dynamic design changes based on uncertainty of material quality and availability. Through the digital thread, material uncertainty can be addressed by introducing non-destructive material qualifying systems that generate novel life cycle data to support CE design activities.

Full support of the CE requires research to connect product life cycle data through the digital thread and retool it in data-driven approaches that support design decision-making. In theory, this can materialize as product and system-level digital twin representations combined with machine learning and AI approaches that are reactive to stimulus from all areas of the product life cycle—for example, changing engineering specifications of in-production products caused by material feedstock quality data combined with machine intelligent representations of the subsequent change propagation. However, a fully responsive design system, reactant to changes in the product life cycle, requires the designer to be within and connected to the product life cycle data loop.

4.3 CHALLENGE 3: DESIGNER IN THE LOOP AND AI DESIGN AGENTS

Designer-in-the-loop is a design-adapted concept of human-in-the-loop. Human-in-the-loop is the hybridization of human cognitive capabilities and technical systems [51] (Not to be confused with human-in-the-loop as a term for human factors design [52]). In complex systems-of-systems domains, such as a CE, human input can incorporate qualitative aspects of product design such as brand recognition, company culture, and subjective input. As such human-in-the-loop concepts are congruent to the personalization of smart manufacturing and other technical systems that are found in late industry 4.0 [53].

In literature, Schwarts et al. [54] explored designer-in-the-loop concepts to introduce machine-aided in-design convergence through a similarity score design loop. This work provides a method to allow designers to iterate with the help of machine learning. However, this method remains a black box where only results (the similarity scores) are interpretable. Furthermore, real-time considerations are lacking and can be critical to product design in a CE.

In electrophysiological sensor placement design, Nittala et al. [55] implemented human-in-the-loop in the optimization process of sensor amount, placement, and type. In the integrated predictive model, an expert user inputs data about a patient. Then the interactive optimizer provides human interpretable data and sensor layouts. The expert user can fine-tune the resultant layout and re-optimize. Although literature exists in the area of connecting humans to technical systems, full realization and application of sociotechnical systems in product life cycle management are still a long way off [51]. This presents an opportunity to define human-machine hybrid systems in product design that focus on information transfer, real-time design, and life cycle response.

In product design for a CE, machine integration must be interpretable, partially supported by human cognition, and accessible by all actors within the product life cycle. This can be especially important when the designer-in-the-loop human input may not come from a design engineer or a design team. In practice, AI design agents may require human input from actors within the life cycle area to stimulate design changes. Machine operators, production engineers, and other non-design-trained humans may need to make design decisions. On the contrary, it is impossible to assume a design engineer possesses absolute knowledge about all *DfX* and product life cycle areas. As such, a research opportunity remains to implement designer-in-the-loop systems that interpret life cycle data for trained designers and simplify design decisions for non-trained workers. The dynamic balance of human interpretability and input with modern machine intelligence can improve interoperability between product design and the rest of the product life cycle, thus, helping introduce temporal approaches to product design.

4.4 CHALLENGE 4: CE DATA-DRIVEN DESIGN METHODS

In Industry 4.0, data-driven design methods have been introduced to supplement designer knowledge during the design process but are challenged by disparate data and have low adaptability to specific design scenarios [56].An author-led literature review in data-driven product design (DDPD) shows that these methods are often product data-scarce and rely on text data (in the form of customer reviews), simulated data or specifically curated data for method validation [57]. A similar review focused on data-driven product design toward intelligent manufacturing also concluded that there is a need to explore the use of product data in DDPD [58]. Although the methods explored in these reviews apply the principles of Knowledge Discovery in Databases (KDD) [59], they are still reliant on human interpretation of new knowledge and trust in the accuracy of machine learning representations. These data-driven design methods also suffer from data quality pitfalls, where data used in design is sparse and disparate. Design data is often hidden behind non-disclosure agreements, intellectual property, confidentiality, national security, and private design repositories. As such, primary design data available to human and AI designers is likely limited to enterprise-based design data. The lack of available design data can prove detrimental to ML and AI's ability to make design decisions or even ascertain meaningful knowledge. As such, it is imperative to consider designer-in-the-loop approaches to consumer product design within the CE.

Applied designer-centric data-driven design tools must be introduced to fully incorporate designer-in-the-loop within the CE. Where challenge 3 focuses on addressing AI and ML challenges with a need for human-machine decision-making hybridization, challenge 4 focuses on developing tools and methods toward human integration in data-rich environments. These design tools should be data-driven from all areas of the product life cycle, simplify knowledge abstraction, utilize human-iterable AI and ML processes, and value real-time human input. Although current research aims to provide data-driven design support and automation methodologies, challenges remain in applied human-machine and ML-based design approaches.

Echoing back to challenge 2, expansion of the digital thread and feeding data back toward product planning is beneficial to DDPD and supports the inclusion of data from all life cycle stages for product development [60]. Also mentioned in challenge 2, digital twin representations of products and life cycle systems can help to facilitate the transfer of data to support product design [61, 62]. Although some aspects of challenge 4 represent the same challenges outlined in challenge 2, additional challenges are caused by the increasing complexity of data storage to support DDPD.

4.5 CHALLENGE 5: CE DESIGN STANDARDS

Standards built to specifically address the CE can provide the structure needed to support data interoperability crucial toward meeting challenges 1 through 4. Currently, the only standard published explicitly toward CE is the BSI Standard 8001 [63]. This standard focuses on framework and guidance for an organization to implement CE principles. However, since the publishing of the BSI CE standard in May 2017, the international standards organization has introduced technical committees focusing on drafting the ISO 59000 series for a CE framework [64].

The ISO 59000 series is broken up into five working groups as part of the technical committee 323. The focus of these groups is establishing a CE framework, exploring business implementation, measuring circularity, introducing CE case studies, and curating a CE-based product data-sheet. This work provides the needed context to define, demonstrate, and measure the CE properly. Working items such as measuring circularity and CE-based product data-sheet have direct applicability toward the realization of product design in the CE. However, explicit product design standards for the CE are needed. For this we propose to bridge explicit CE standards to existing standards around digital twin frameworks for manufacturing (ISO 23247-1:2021) and data representations (ISO 6983,ANSI/MTC1.4-2018,ISO 10303) [65–68].

Beyond connecting existing standards to CE standard development, standards may be developed to establish adaptive data sources embedded and representative of past, present, and future product life cycles. In essence, standardizing product genealogy, passports, adaptive data representations, along a digital thread can improve product data availability and expansion of product life cycle assessment scope to consider past, present, and future life cycles and depart from classic cradle-to-grave models.

Toward *Design for the CE*, technical committees can focus on standard development for each *DfX* topic relevant to the CE. Improving end-of-life standards and introducing assembly/disassembly standards can aid in the recapture of material streams for future product life cycles. The introduction of CE-centric standards can aid in limiting the complexity of designing for CE imperative *DfX* areas. Currently, several standards can be co-opted toward meeting CE *DfX* principles. ISO 14000–environment management series, along with ISO 9000 (quality), 50001 (energy), and ISO 20140-1:2019 (automation systems and integration), can be used to aid in measuring and standardizing management and measurements in the CE [69–75]. In current work, these standards are already being applied in support of sustainability [76].

5 A CIRCULAR PRODUCT DESIGN CONVERGENCE MODEL

In Figure 4, we introduce a preliminary circular product design convergence (CPDC) model that is focused on improving design convergence activities in the CE. This model provides a simplistic understanding of how designers, simple and complex computation systems, real-time digital twins, and improved data streams can interact to enhance data-driven design practices. Figure 4 is separated into three connected systems that each represent a research opportunity: Digital twins in green, in pink machine-centric approaches (machine learning, Design Automation, Knowledge Discovery in Databases, and Optimization), and complex designer-in-the-loop AI design agents in blue.

5.1 DIGITAL TWINS

First, to apply the CE product design convergence model, we need to create a digital twin representation of product assets. This digital twin takes in digital thread data–connected life cycle data– to digitally represent real-time changes to the physical product during different life cycle activities. We envision this as real-time data processing that can apply human-interpretable, visual representations of the product and various product properties. In theory, this can be a real-time graphical representation of the number of production units in each life cycle area, assembly stage descriptors, heat map overlays indicating failure components, and consumer use and disposal analytics. The framework for a product life cycle digital twin should be robust and cooperate with other smart manufacturing digital twins. The CPDC model shows that product digital twin representations can inform how engineering specifications are being met and if those targets need to be reevaluated. The product digital twin can provide human accessible data representation and real-time decision making that bridge the initial gaps in sociotechnical systems. However, though knowledge-rich, this proposed digital twin product representation still relies on human-centric manual decision-making. Thus, it does not directly engage in complex machine learning methods that designers can use to aid design automation, evaluation, and optimization.

5.2 MACHINE-CENTRIC APPROACHES

To enhance machine-aided approaches to design, digital twin data and digital thread can be applied to existing and novel data-driven approaches. Here machine learning, design automation, and optimization methods can generate and evaluate design concepts that are reactive to temporal data streamed from the product digital twin. Combining smart machine systems with digital twin representations can improve virtual-physical data fusion, extract embedded knowledge, and aid design decision-making. Similar concepts of fusing digital twins and data learning methods have been introduced to smart manufacturing systems to aid in continuous system improvement [77]. In a similar context, the fusion of data learning methods to product digital twins can result in continued design improvements that respond to life cycles stimulus. Classification, automation, and optimization knowledge extracted via machine learning can be analyzed in the context of the digital twin, expanding the amount of knowledge available to the designer when making design changes.

5.3 DESIGNER-IN-THE-LOOP AI DESIGN AGENTS

Design becomes a challenge of integrating human understanding with the lessons derived from machine learning, taking advantage of both systems of knowledge. The previous design paradigm which has been characterized as subjective and speculative becomes data-driven while still being guided by the qualitative knowledge provided by the human. The AI Design Agent of the CPDC model is the hybridization of human intuition to influence the previously introduced technically-gained insights. Including the concept designer-in-the-loop can help improve machine-aided design convergence through iteration by introducing qualitative data sources. In practice, human input of qualitative data can guide the feasibility of AI-driven design solutions by converging on designs that meet company identity, enterprise manufacturing capabilities, standards, and regulations. In all cases, applying human-in-the-loop concepts to the CPDC model can increase the velocity at which AI design agents are optimized to converge on acceptable design decisions while reducing the need for future human interventions.

6 CONCLUSION

The Circular Economy is defined as an economic system that maximizes the time resources remain in the economy, eliminates waste, and increases resource utility with explicit consideration of triple-bottom-line sustainability. The realization and application of the CE-system inherit challenges that have yet to be solved in the current applications of the production economy. One such issue is facilitating data-driven design practices that

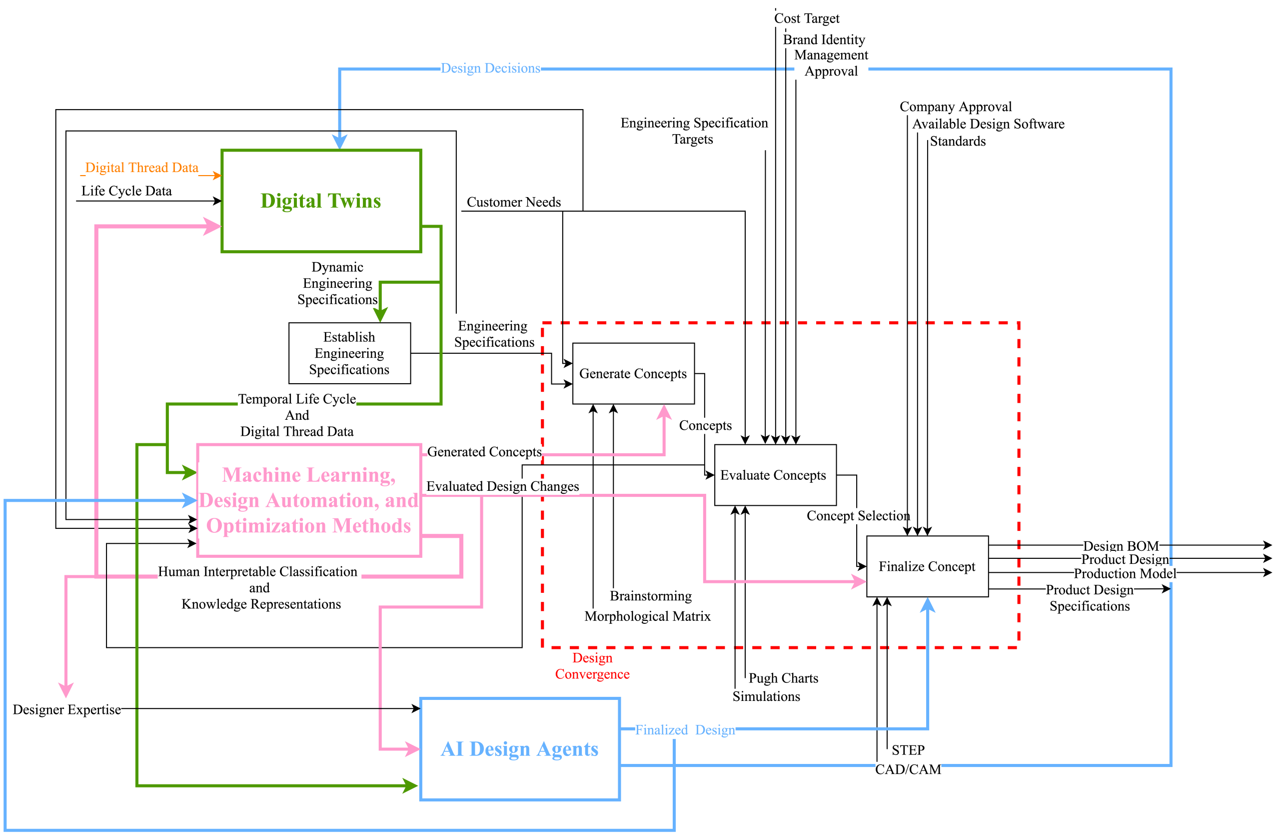

FIGURE 4: A Design Convergence Model For a *Circular Economy*.

leverage data sourced from each product life cycle area. In this paper, we explore the challenges in adapting product design practices to the CE. Then we introduce a preliminary circular product design convergence model that can be a framework for exploring standards-driven and validated solutions to these challenges.

Product design is classically a manual, subjective, and speculative process that relies on the cognitive and internal knowledge of the product designer. To combat this, multi-disciplinary design teams have been introduced to supplement the knowledge needed to successfully design products within the current complex global socioeconomic system. Other knowledge supplementation solutions include data-driven product design methods. However, these methods are limited by product data availability. Often data-driven product design literature uses mined text data, simulation data, or purposely curated data to validate the method. Transitions to the CE require solving the data-disparity challenges that inhibit robust data-driven product design systems. In addition to data translation, research is needed towards designer-in-the-loop design systems that allow dynamic product design activities stimulated by real-time data from all areas of the product life cycles. Lastly, *design-for-the-CE* is likely an amalgamation of many *DfX* terms. As such, we need to identify the critical *DfX* areas that apply to CE. The set of challenges needed to be met to adapt consumer product design to the CE are:

1. Consolidation and identification of *DfX* areas critical to the CE
2. Realization of a digital thread to the design activities
3. Incorporation of designer-in-the-loop and AI design agents
4. Introduction of CE data-driven design methods
5. Development of CE design standards

In Figure 4, we introduce a circular product design convergence model that shows a CE product design system that solves the last four challenges. First, a digital twin is created which takes in life cycle and digital thread data to create a temporal representation of a product in various product life cycle stages. The real-time data allows the digital twin to express changes to engineering specification targets and thus allows a designer to make dynamic design changes. Second, Machine learning methods can be leveraged to extract meaningful knowledge from the product life cycle that is then reflected in the product digital twin, aid in generating product design concepts, and help designers evaluate concepts for dynamic decision making in reaction to real-time data. Finally, designer-in-the-loop AI design agents are introduced to integrate subjective aspects of product design with the machine learnings. The AI design agent can interpret human designer input that can be used to modify machine learning systems, guide feasibility of design decisions, and help finalize design changes.

The circular product design convergence model presented is visionary and achieving its scope is non-trivial. The CPDC model does not evaluate nor consider the tremendous work needed to realize a digital thread to product design. Furthermore, the model does not prioritize the importance of individual data sources within the design process. Addressing challenge 1 (consolidation and identification of *DfX* areas critical to the CE) will provide guidance for the model to weight data in accordance to most crucial *DfX* goals. This can be especially important in making design changes that affect *DfX* correlated engineering specifications, especially those that result in adversarial interactions between engineering specifications. These adversarial interactions must be considered.

The challenges, in this manuscript, present an expansive opportunity to explore and solve the adaptive changes needed for product design applied for the CE. In future work, we can look at defining the *DfX* characteristics of *Design for the Circular Economy*, and developing a framework for measuring and balancing the importance of each sub *DfX* area. From there, we can define life cycle data sources for each *DfX* area. We can also seek to define measurement methods and standards as a means to transmit the identified CE *DfX* data to product design activities, thereby expanding the digital thread of product data to other life cycle stages. This work can continue the standardization of such data representations to maintain transferability and interoperability between life cycle areas. Finally, we can explore the introduction of a digital twin, machine learning, and AI design agent systems that can use life cycle data in applied CE product design approaches such as the one theorized in the CPDC model.

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