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Causal AI-powered Digital Product Passports for enabling a circular and sustainable manufacturing ecosystem

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Abstract

Digital product passport (DPP) has been recently introduced by policymakers (e.g., the European Commission) to advance sustainable business practices towards a circular economy (CE). As a newly introduced concept, DPP is still relatively high-level and vague. Therefore, its definition, information flow architecture, what relevant information needs to be stored, and how to use such information in the context of a circular and sustainable manufacturing ecosystem, etc., are still open research questions. This paper addresses these research questions by proposing a novel conceptual framework for DPP, facilitating seamless information exchanges among CE stakeholders, and providing a transparent and trustworthy basis for decision-making. Causal AI utilisation is proposed to extract causal relationships among sustainability/circularity KPIs comprehensively, encompassing raw material supply chain, circularity-compliant product design, manufacturing optimisation on the shop floor, and after-sale product usage optimisation. Seamless information exchange will be achieved through semantic interoperability and a comprehensive model of the whole supply chain by employing an ontology model. The causal AI approach is proposed to identify causalities among KPIs and other factors to predict environmental impacts. This way, a causal model integrating domain expert knowledge and causality discovered from measured data will increase the transparency/explainability of prediction/decision made by machine learning algorithms.

Keywords: Sustainability; Circularity; Manufacturing; Digital Twin (DT); Digital Product Passport; Causal AI; Ontologies

1. Introduction

Many existing manufacturing ecosystems still adhere to a linear manufacturing model. Challenges such as tighter environmental standards and changing consumer expectations drive organisations to embrace an alternative manufacturing model that guarantees environmental sustainability. To address these challenges, the concept of sustainable and circular manufacturing has already been introduced in the manufacturing sector [1]. Sustainable manufacturing aims to deal with the challenges by minimising the environmental impacts due to products, processes, and systems through optimal use of energy and resources. Meanwhile, circular manufacturing or circular economy (CE) aims to maintain the value of products, components, materials, and resources in the economy for as long as possible [2].

Nevertheless, for products to retain their value for an extended time, their constituent parts and materials need to be closely and automatically monitored. Original equipment manufacturers (OEMs) that have access to this type of information can then better understand the design requirements for a more sustainable and circular production system. Many products and OEM parts far exceed the warranties provided and may enter the “end-of-life” (EOL) stage prematurely. In addition, recyclers may benefit from having life-cycle performance data accessible to them so that they can better understand, design, and operate effective recycling systems with reduced materials cross-contamination.

A Digital Product Passport (DPP) concept has been recently introduced by policymakers such as the European Commission [3], as a strategic instrument to improve circularity, sustainability, agility, quality, and resilience to external and internal influences. It is believed that DPP will make data easily available for potential unskilled workers in the form of reports and graphical insights. However, some research questions regarding (*i*) information flow architecture, (*ii*) how to seamlessly integrate data from different sources (*iii*) what relevant information needs to be stored in the DPP, (*iv*) how to use such information in the context of circular and sustainable manufacturing ecosystems, (*v*) how to ensure the DPP is interoperable across the whole product’s life cycle, and some more, are still open.

Based on those research questions, this study aims to propose a novel conceptual framework to guide developers to establish a DPP that gives holistic insights not only into the manufacturing processes and product quality but also into environmental Key Performance Indicators (KPIs) resulting from all the stages in the whole life cycle of a product. Notably, the DPP should also provide some feedback/recommendations for process optimisation of different product life cycle stages including the design, manufacturing, transportation, usage phase and after-EOL phase for circularity.

The framework conceptualisation is driven by several factors as detailed in the following. Life cycle assessment (LCA) is a common practice and has become an important step in sustainable manufacturing to identify, evaluate and assess the environmental impact during the whole life cycle of a product. However, the current concepts do not consider the raw material supply, the design phase, or environmental KPIs (e.g., the greenhouse gas (GHG) emissions) during the manufacturing process, the usage phase, and the after-usage phase (e.g., the circularity/recovery process). Yet, no digital technologies that allow for automated circularity/recovery recommendations for the user to make informed decisions for a product that has reached the EOL. AI is a promising technique to respond to the query that can leverage its capabilities to analyse, interpret, and extract valuable insights from large datasets. However, conventional AI merely relies on correlations among data, where the correlation does not necessarily imply causation. An intelligent technique that is capable of understanding and modelling cause-and-effect relationships is necessary. The adoption of Causal AI that allows us to gain insights from semantically interoperable data will enhance the interpretability, traceability, and trustworthiness of insights for decision-making within CE activities. At the same time, the proposed DPP should be equipped with interoperability capabilities for reducing the costs, time, and risks associated with developing new CE business models. This can be achieved through the implementation of the FAIR data principles (Findable, Accessible, Interoperable, and Reusable). Ultimately, the integration of circular and sustainable manufacturing concepts inevitably reduces the reliance on finite resources and minimises pollution. Furthermore, such integration can lead to a novel circular compliant business model and ecosystem powered by sustainable energy.

The remainder of this paper is structured as follows. Section 2 critically reviews existing works in the literature and identifies research gaps. Section 3 proposes a new conceptual framework based on the research gaps identified in the previous section. Section 4 critically discusses the proposed framework. Finally, the conclusions and future work are discussed in Section 5.

2. Related Work

The significant role of the DPP in the circular economy has been extensively discussed across multiple sectors, including academia, industry, and policymakers. Despite these efforts, implementing DPP still poses challenges, primarily due to the various data formats provided by various CE stakeholders that lead to challenges in achieving seamless data sharing and the limited accessibility to such data [4]. These issues contribute to a lack of transparency and reliability in decision-making processes within CE activities. Presently, there is a notable gap in research focused on developing a standardised information model for DPP that semantically describes products and fosters a shared understanding among stakeholders [5]. While ontologies have been employed to communicate complex information, existing ones may not always be suitable, especially in contexts with new problems or industries [6,7]. A recent research advancement has introduced an ontology to offer standardised vocabularies and taxonomy to assess circularity in the automotive industry [8]. Causal AI has been discussed in the literature, for example, for root-cause analysis of machine failures using monitoring data from factory sensors, leading to significant cost savings [9]. Causal discovery has given benefits to the industry such as for predictive maintenance and extracting causality in time series datasets because it provides a deeper understanding of data sets compared to traditional AI techniques. Other articles explore the practical application of causal discovery in manufacturing, showcasing successful results summarised with the assistance of domain experts [10,11]. Further research articles investigate causal discovery and adapt algorithms effectively to the complexities associated with diverse data types, a critical aspect of circular economy research [12,13]. The research gap arises from the absence of an integrated Causal AI tool for the CE domain, which would combine expert-modelled and automatically generated causal relationships from diverse datasets facilitated by the DPP. This integration involves constructing causal graphs using causal discovery algorithms and directed acyclic graph (DAG) merging techniques using advanced linguistic and structure-based approaches.

The complexity of products has tremendously increased over the last decades, and so has their design process, due to the necessity to meet the stringent performance and cost requirements in ever shorter time-to-market circumstances. For instance, model-based systems engineering (MBSE) [14] (to deal with the multi-disciplinary nature of today's systems), design structure matrices [15], design space exploration [16] and generative AI, are some technological examples that are used to deal with the complexity of the design process. Fundamentally, this complexity is often broken down into three aspects, namely (i) the multi-objective and multi-constraint nature of the design problem, (ii) the ever-growing number of design decisions that need to be considered with dependencies between them, and (iii) the various uncertainties that are inherent to the design process, stemming from uncertainties due to badly understood phenomena, over unknown usage of the products, etc. When design teams start considering sustainability, the complexity of the design process further increases by an order of magnitude. This is why the uncertainties explode, for instance, different *ReX* strategies [17] in the after-use phase lead to various impacts, and LCA results are often inaccurate and only available when detailed design is performed [18].

To produce acceptable product quality with optimal energy consumption, cost, and time, it is necessary to predetermine the processing sequence. Every process has a unique process characteristic and capabilities and there are no guidelines/standards to optimise the sequence and the allocated tolerance. Therefore, before the manufacturing process starts, engineers need to determine the targeted tolerance at each processing step to meet the final tolerance of the product. The common practice is initiated based on the design for manufacturing followed by the analysis of geometric dimensioning of tolerancing considering the process capability analysis of every manufacturing stage with the objective function of tolerance allocation is the sum of the cost-tolerance functions for the dimensions of a tolerance chain [19]. However, when there are some deviations in the process parameters, some machining stages might not be able to achieve the targeted tolerance. The research gap lies in the need for a real-time tolerance control technique that minimises cost-tolerance functions by continuously monitoring processes and predicting machine conditions.

Historical data or secondary data sources are commonly used in the existing methodology and tools for both sustainability analysis through LCA and circularity analysis to estimate established indicators [20]. Several drawbacks in the existing LCA tools were identified and well-known. Recent work addresses some of the drawbacks by developing a real-time LCA tool using a cyber-physical system approach to monitor and track global warming potential (GWP) calculated from measured energy and material consumption during the manufacturing processes [21]. However, the method and tool do not consider the raw material supply, the design phase, the GHG emissions during the manufacturing process, the usage phase, and the after-usage phase (e.g., circularity/recovery process). Lifetime Extension Strategies supported with digital technologies are enablers of CE to achieve sustainable development goals [22,23]. Required digital technologies such as algorithms/software tools and digital twin (DT) for lifetime estimation of an asset or product have been implemented in the industry for various predictive maintenance (PdM) applications [24,25]. A product recovery multi-criteria decision tool was developed in [2] to evaluate product circularity strategies when a product has reached the EOL. The tool uses an integrated approach by considering simultaneously technical, economic, environmental, business, and societal aspects. However, it does not consider the actual health conditions of the product's components and the uncertainty due to the stochastic nature of the components' degradation which should be estimated from the sensor data. Therefore, the decision made with the existing tools is prone to erroneous. Besides, the tool does not automatically recommend a circularity strategy (e.g., Reuse, Remanufacture, Recycle, etc.) for a given product's component, which can be very helpful for the user to make a quick and effective decision.

In summary, it can be stated that there is a significant gap in the scientific literature concerning a methodology and framework for establishing a transparent and interoperable DPP providing relevant environmental KPIs required to optimise the whole product's life cycle from product design, manufacturing, transportation, usage to after EOL.

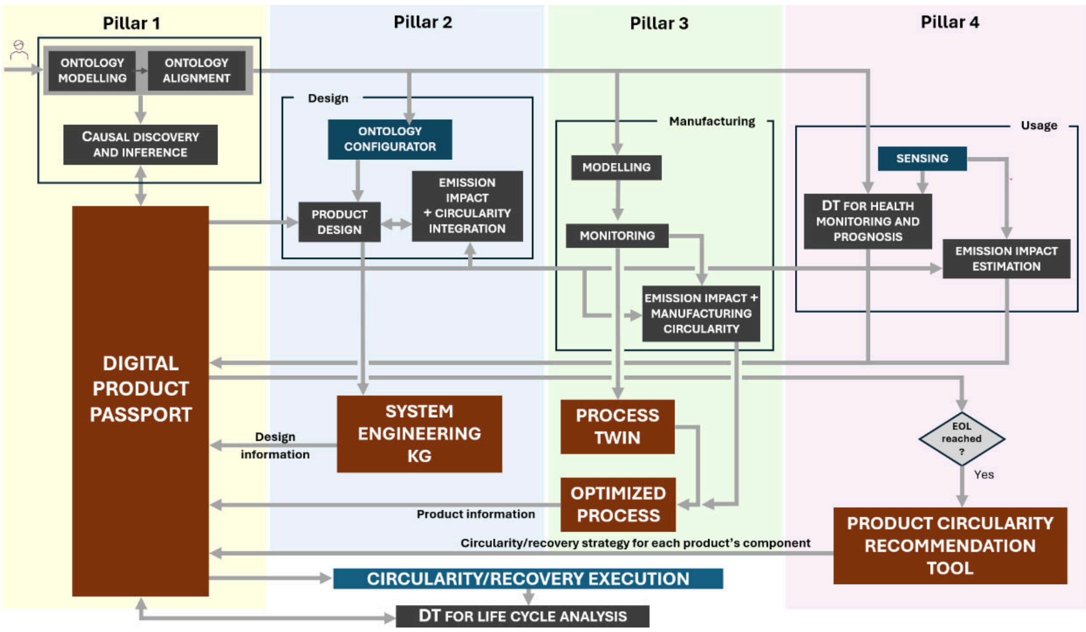

Fig. 1. Conceptual framework of Causal-AI powered Digital Product Passport (DPP).

3. Conceptual Framework

Four important pillars to establish a transparent and interoperable DPP that provides relevant environmental KPIs for the whole product's life cycle optimisation were identified in this research. The pillar selection is motivated by the drivers discussed in Section 1 and the gaps identified in the scientific literature in Section 2. Transparency and interoperability of the DPP are achieved through causal AI and ontology modelling. Also, relevant digital tools for each pillar have been identified to achieve this purpose. All these elements are crafted into a framework shown in Fig. 1. The following sub-section provides more details of each pillar.

3.1. Pillar 1: Causal AI-Powered DPP

Pillar 1 comprises five key components and three interfaces. It plays a crucial role in shaping the information landscape and ensuring information traceability through DPP. The primary components include (1) Ontology, which defines the vocabularies and structure of the information schema utilised in the DPP; (2) Graph Alignment Tool, facilitating the alignment and interlinking of graphs, including ontologies and knowledge graph (KG) alignment/interlinking. It plays a pivotal role in aligning the *systems engineering KG* (SE-KG), see Pillar 2, with the main KG; (3) Data FAIRification tool to FAIRify diverse data sources with varying structures, including tabular, text, and image formats and integrate the results into the main KG; (4) Causal AI Tool, designed to enable the causal analysis of data collected and linked through the DPP. This tool integrates essential functionalities, such as causal discovery algorithms for the automatic generation of causal graphs from data, causal inference algorithms for quantifying causal effects, and an interface seamlessly incorporating the results of causal inference into the main KG; (5) The main KG, serving as the information backbone for the DPP with its vocabularies and structure aligned with the ontology; The interfaces consist of (5) Interface for domain experts, aiding in ontology modelling based on domain knowledge and validation of graph alignment results; (6) Data interface, facilitating the ingest of data from across the product lifecycle; (7) KG interface, acting as the bridge to other KGs to be linked with the main KG.

3.2. Pillar 2: Circularity Compliant Product Design

Pillar 2 deals with the tremendous challenge of integrating sustainability in general and circularity in particular in the product design process or New Product Development (NPD) process. The core idea is to bring 3 essential ingredients together: i) an MBSE approach that allows formal representation of main KPIs and constraints of the design process allowing to deal with the complex and multi-disciplinary nature of today's product design, also in the early phase (starting with the requirements); ii) a formal representation of and ways to calculate product circularity indicators, based on the various *ReX* strategies and iii) a risk-management strategy that allows to explicitly represent and, where necessary, reduce the uncertainties that are inherent to circular design based on available data to mitigate the risks that are typical for the early stages of the product design. These 3 ingredients come together in the SE-KG, a KG in which nodes represent design decisions and KPIs, and edges represent (uncertain) relationships between design decisions mutually on the one hand, and design decisions and performance, cost, and circularity KPIs on the other hand. As the nodes from the SE-KG are also linked to all available data sources covering the complete lifecycle of the products, it becomes possible to explicitly model and mitigate this uncertainty. To avoid building this KG from scratch, an ontology configurator will allow the creation of a company/value chain-specific KG starting from a generic ontology. Finally, the causal relationships that are unveiled by the Causal AI Tool (see Pillar 1) will be merged with the expert knowledge manually inserted in the SE-KG to ensure a complete representation of the various relationships that need to be accounted for in the design process.

3.3. Pillar 3: Digital Twinning & Manufacturing Recommendation

DTs offer services such as prediction, diagnosis, prognosis, and prescription through the digital representation of production systems. For example, the utilisation of simulation, particularly discrete event simulation, is crucial in modelling manufacturing process flows and using the material flow routing network as a skeleton for performing targeted predictions. Hence, simulation models represent a foundational component in DTs. Besides, given the ever-repeating difficulties that companies face in equipping their employees with advanced digital skills, the manual generation of DTs may compromise and slow down the temporal flow of information, from shop-floor data to actionable recommendations. Thus, the automated generation and adaptation of digital models emerge as the cornerstone for comprehensive DTs across the entire value chain. While rule-based configurators are costly solutions that create con-text-dependent simulation models within rigid frameworks, data-driven approaches use event data logs from information systems to automatically discover both process and system models. These approaches, however, reveal limitations when applied to manufacturing process chains characterised by complex production policies, changing item identifiers along the value chain, and finite capacity resources. Integration of DTs with emission impact models provides an end-to-end digital twinning solution that overcomes the limitations of approaches targeting the twinning of single system elements. The main idea is to use the DPP as a horizontal and impartial integration element that effectively interfaces between resource-, process-, and system-level digital models, providing both the means for the generation and validation of these models at the same time. Indeed, given that all perspectives must be compliant with the DPP information simultaneously, the overall coherence is guaranteed. Moreover, this pillar also addresses the capabilities for integrating end-to-end circular-compliant product-to-process design solutions, notably the interface between tolerance-related quality requirements from upstream to downstream value chain processes.

3.4. Pillar 4: Digital Twinning for Lifecycle Analysis, Lifetime Estimation and Circularity Recommendation

This pillar aims to address the limitations of both the existing methodology and tools for LCA and circularity analysis that rely on historical data, or secondary data sources (e.g., public data). By using sensor data (i.e., primary data source) combined with the Causal AI from Pillar 1, the emissions impact for each stage in the product lifecycle, from resources to material processing, to product manufacturing, to product distribution, to product usage, and product EOL, can be estimated more accurately. Consequently, the estimation uncertainty is reduced by using the primary data sources. This pillar suggests that the emission impact estimation using sensor data and the causal AI is targeted on the 3 main stages, namely (i) the product design stage, (ii) the manufacturing stage, and (iii) the usage stage. Furthermore, the emission impact estimates for each stage will be aggregated and eventually visualised by a DT for LCA. Thanks to the causal AI, the factors contributing to the emission impact of each stage can be traced back, thus DT for LCA can provide actionable insights to the corresponding stakeholders. This way, effective actions for each stage can be taken to reduce the emissions as much as possible without affecting the organisation's goal. Meanwhile, the components of a product during usage might experience different degradation levels. DTs for health monitoring, diagnostics and prognostics will be necessary for implementing the PdM strategy to extend the lifetime of the product. However, there is a moment in time at which extending the product lifetime is no longer beneficial in terms of economy, society, environment, and regulation. In this scenario, the product has reached the EOL. To ensure that the value of the product's components can be maximised, a software tool that can provide recommendations for circularity strategy (e.g., recycling, remanufacturing, refurbishing, reuse, etc) for each product's component is necessary.

4. Discussion

This section presents a novel conceptual framework that focuses on an innovative manufacturing approach that incorporates causal AI features into DPPs. The DPP framework enables the tracking of carbon footprint, energy consumption, and waste throughout the product lifecycle. The framework also comprises a set of novel models, algorithms, and digital tools serving multiple purposes such as supporting new circularity-compliant product design, optimising manufacturing processes to reduce waste, energy consumption, and carbon emissions, and accurately predicting the carbon emissions impact during different stages of the product lifecycle. Moreover, these tools automatically recommend circularity strategies for products that have reached the EOL.

Our approach also integrates sustainability and circularity considerations into the business model. Thus, it holds significant technological implications. Positioning the framework at the central point of sustainable practices enables eco-friendly manufacturing processes and contributes to a greener industry. This shift not only minimises environmental impacts, but also opens doors to new economic opportunities and business models. The novel digital tools within the framework will reform manufacturing ecosystems. When integrated with existing software solutions, these tools enhance services, provide added value to current customers, and attract new potential customers. The digital tools and their novel business models introduce a top-down DPP integration approach, achieving streamlined information flows within various levels of the supply chain. This transformation enables enhanced efficiency, reduced costs, and increased profitability for businesses adopting this innovative model. By streamlining communication and data exchange through DPP, the framework empowers agile and responsive supply chains, ultimately benefiting both businesses and consumers.

The DPP benefits consumers by providing clear information about product origins, fostering trust, and promoting the adoption of sustainable and circular products. By offering transparency in the manufacturing process, consumers can make more informed decisions that align with their values and preferences. Furthermore, the integration of carbon footprint considerations into business practices influences businesses to adopt eco-friendly practices, leading to a reduction in overall environmental impact. Through optimisation of design, manufacturing, and circularity strategies, the carbon emissions reduction is estimated between 5-25% which contributes to a more sustainable future. Additionally, the implementation of automated circularity recommendation tools improves informed decision-making for circularity strategies of products, further enhancing their environmental sustainability.

A few potential challenges are anticipated when implementing the proposed framework in practice. It requires extensive data collection, which may include sensitive information. A primary challenge is ensuring robust protection of this data against unauthorised access and breaches. Therefore, it is essential to establish clear regulations governing who can access this data, with a particular focus on protecting consumer privacy. However, regulations variability across different jurisdictions makes international cooperation and the global trade of goods incorporating the framework complicated. Additionally, many regions lack comprehensive legal frameworks that regulate the use and sharing of data through DPPs. Engaging consumers and stakeholders presents a challenge, often due to a lack of awareness about the framework's benefits. Providing sufficient economic incentives could significantly enhance the adoption of the framework. Furthermore, the compatibility among different machining stages is a crucial factor at the lower level. Interfaces connecting one component to other system components for seamless data retrieval and exchanges, including APIs, protocols, and communication channels, should be considered aiming for optimal interoperability.

5. Conclusion and Future Work

A novel conceptual framework for Digital Product Passport (DPP) designed through causal AI and ontology modelling has been developed and discussed in the paper. The framework consists of four pillars including (i) *Causal AI-powered DPP*, (ii) *Circularity Compliant Product Design*, (iii) *Digital Twinning & Manufacturing Recommendation*, and (iv) *Digital Twinning for Lifecycle Analysis, Lifetime Estimation and Circularity Recommendation*, of which relevant and necessary digital technologies for every pillar have been identified in this study.

Future work will be to implement the framework, develop the identified digital technologies and validate the proposed framework and the technologies using industrial use cases.

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