Unlocking Strategic Value from Digital Product Passports by Leveraging AI

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Abbreviations

AI	Artificial Intelligence
BDP	Battery Digital Passport
BMS	Battery Management System
CAD	Computer-Aided Design
DLT	Distributed Ledger Technology
DPP	Digital Product Passport
EC	European Comission
EoL	End-of-Life
ESG	Environmental, Social and Governance
EU	European Union
EVB	Electric Vehicle Battery
LCA	Life Cycle Assessment
LLM	Large Language Models
ML	Machine Learning
NLP	Natural Language Processing
OEM	Original Equipment Manufacturer
RUL	Remaining Useful Life
SoC	State of Charge
SoCE	State of Certified Energy
SoH	State of Health

Executive Summary

Digital Product Passports (DPPs) represent a transformative shift in regulatory and business practices. While mandated under emerging EU frameworks, viewing DPPs solely as a compliance requirement is a missed opportunity. Organisations that adopt DPPs strategically can unlock substantial value beyond regulatory requirements, leveraging them to differentiate products, strengthen customer loyalty, and secure a competitive advantage.

DPPs deliver benefits across multiple dimensions: improved supply chain transparency and traceability, enhanced risk management, and opportunities for environmental impact reduction aligned with global sustainability goals. They enable product innovation and new circular business models such as resale, repair, and leasing, while increasing overall product value. Verified product data fosters consumer trust and brand reputation, combats counterfeiting, and supports Environmental, Social and Governance (ESG) commitments.

Across the passport lifecycle, AI transforms fragmented inputs from diverse stakeholders into secure, auditable insight. Capabilities include automated data ingestion and validation, predictive health and end-of-life decisioning, evidence-based carbon accounting, supply-chain risk scanning, quality control, adaptive disassembly, and fraud detection.

DPP adoption offers significant strategic and operational benefits for businesses. It enables organisations to leverage DPP data for internal audits and quality assurance, improving operational efficiency and transparency across the supply chain. By implementing DPPs ahead of regulatory deadlines, companies can avoid the risks associated with last-minute regulatory pressure and potential penalties. Moreover, early adopters gain a competitive edge by positioning themselves as industry leaders in sustainability and innovation, strengthening brand reputation and customer trust while future-proofing their operations.

Key takeaways:

- DPPs are a strategic value platform, not a box-ticking exercise. Done right, they drive product differentiation, build customer trust, enable circular models, and deter counterfeits.
- Early DPP adoption offers advantage. Integrating DPPs ahead of deadlines reduces last-minute risks and penalties, improves internal audits, and positions adopters as leaders in sustainability and innovation.
- Actor dynamics matter. Different value chain actors have varying appetites and reluctance to share data. Addressing intellectual property/privacy concerns and standardisation gaps is essential to improve data availability and quality.
- AI is a key enabler across the passport lifecycle. It converts fragmented lifecycle data into secure, auditable insights, scaling DPPs and unlocking value beyond compliance.
- Security drives participation. Robust cybersecurity and levelled access increase trust and reduce reluctance to share sensitive data.

1. Introduction

As the Digital Product Passport (DPP) becomes a regulatory requirement, it is still often perceived as a mere compliance exercise. This white paper challenges that perception by illustrating the broader value DPPs can offer. It examines the role of AI and cybersecurity within the context of Electric Vehicle Battery (EVB) DPPs, known as Battery Digital Passports (BDPs), providing insight into the potential they hold for improving system performance and building trust. While BDPs are used as the reference example in this white paper, the analysis, conclusions, and recommendations are intended to be universally applicable across products.

A DPP is a digital record of information regarding a product's full life cycle, from constituent raw materials to end-of-life (Figure 1). It contains data that is useful for calculating key performance indicators and assessing environmental impacts - enabling informed product decisions and encourage the reuse, repurposing, and repair of components.

Product lifecycle stages

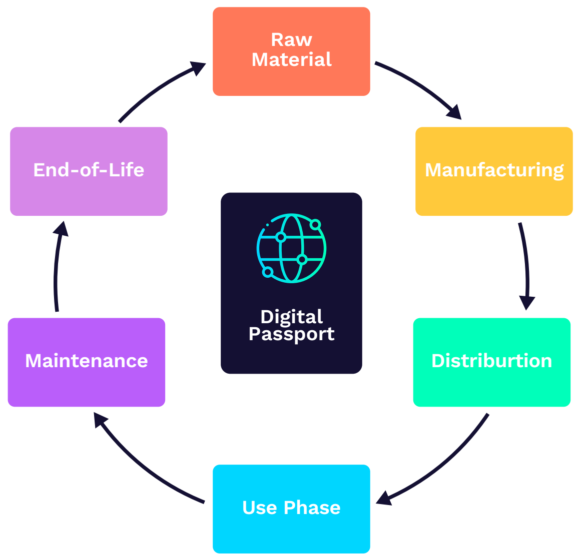


Figure 1: Full product life cycle and constituent stages covered by a DPP.

DPPs are in the process of being rolled out for various products and industries. From 2027 DPPs will be required for batteries placed on the European market, including the EVBs. Between 2026 and 2030 there will be a gradual expansion of digital passport regulations to approximately 30 different product categories (including: apparel, electronics, construction materials). [1]

2. Beyond a compliance checklist

Under the EU Battery Regulation 2023/1542 [2], all batteries sold in the EU must demonstrate sustainability and safety, and this regulation introduced the BDP. The minimum data required by the EU regulations for the BDP contains technical, environmental, and regulatory information about batteries, covering their specifications, manufacturing details, material composition, performance metrics, lifecycle data, safety features, and compliance documentation [2]. Please refer to Table 3 in the Appendix for the full list of minimum data required by EU regulations, as well as the actors access to this data.

Rather than a mere compliance task, EU battery regulation represents a strategic opportunity for businesses. For UK companies selling into European markets, non-compliance could lead to blocked exports and lost revenue, as well as diminished customer trust due to lack of detailed product information. However, treating DPPs as a mere box-ticking exercise misses their true potential. When implemented effectively, DPPs can add significant value to businesses, customers, and drive positive sustainability outcomes for the planet.

The key benefits of DPP implementation that apply across sectors include:

- Improved supply chain management through better visibility and traceability of components and materials.
- Enhanced risk management for sourcing, authenticity, and regulatory compliance.
- Opportunities for product innovation by gaining deeper insights into actual performance and lifespan.
- Increased product value and potential new business models based on subscription, lease, and resale services.
- Increased consumer trust and stronger brand reputation by providing transparency on material origins, environmental impact, and end-of-life options.
- Counterfeit prevention by providing each product with a tamper-proof digital identity, secured records, and instant consumer verification throughout the entire supply chain.
- Improved product sustainability & circularity:
  - Lifecycle data collection on recyclability and environmental impact, supporting the transition to a circular economy.
  - Enabling reuse and remanufacturing to reduce material costs and promote circular business models.
  - Environmental impact reduction through data visibility, allowing informed actions to minimise footprint.
  - Protection against greenwashing by verifying sustainability claims, reducing reputational and financial risks from false advertising.

3. Data Appetite & Data Sharing Reluctance

All actors involved throughout the battery value chain and who require access to specific data have been sorted into five categories in the EU Battery Regulation [2]. Table 1 breaks down the actor names referred to in this white paper and the EU regulation equivalent, as well as a brief description of their role.

Table 1: Actor categories and definitions.

EU Regulations

	Actor Name Referenced	Description
Member of the Public	Customers	Members of the public with an interest in purchasing a battery or viewing battery data.
2	Battery Manufacturer	Companies who produce battery packs hold design and composition data.
3	Original Equipment Manufacturer (OEM)	Vehicle manufacturers responsible for integrating battery packs into vehicles who own the battery once installed, and on whom the responsibility of the DPP lies.
4	Second-life operators	Actors responsible for taking end-of-first-life batteries, assessing their conditions and repurposing them.
5	Recyclers	Actors responsible for end-of-life processing of batteries to recover valuable materials and ensure safe disposal of hazardous components.
6	Service Providers	All entities responsible for maintenance, diagnostics and repair.
	Transport/storage	Logistics companies who handle transport of batteries, and warehousing companies who store companies throughout different stages.
The Commission	Regulators	The European Commission who are driving the EU Batteries Regulation and authorities responsible for compliance checks.
Notified Bodies, Market Surveillance Authorities	Auditors	Independent or third-body entities responsible for assessing, notifying and monitoring of conformity assessments.

The EU battery regulation requires data across the entire value chain, involving multiple actors with varying interests and willingness to share information. These differences directly impact the quality of metrics and benefits derived from the DPP. Actor engagement and reluctance should therefore be considered early in DPP design and AI use case prioritisation.

This section investigates the actor interest (referred to as 'appetite') in accessing key data fields for the AI use cases discussed in Section 5, actors relevant for submitting said data, and any reluctance from these actors; and how implementation of AI and cybersecurity practices can influence this. Findings are taken from case studies carried by researchers with relevant companies and industry experts [3], and key findings are summarised in Table 2 below.

Table 2: Useful data, actors with interest in accessing and actors responsible for submitting data. Reluctance refers to whether relevant actors have reasons to resist sharing data, appetite refers to the level of interest of actors, calculated as an average across all actors. Taken from a study conducted with relevant companies and experts. [3]

Data	Actors with Interest in Accessing Data	Relevant Actor for Data Submission	Reluctance	Appetite
Battery chemistry	Battery manufacturer, OEM, Recyclers, Second-life technicians	Battery manufacturer / OEM	Yes	High
Product composition & structure (modules/cells/ dimensions)	Battery manufacturer, OEM, Recyclers, Second-life technicians	Battery manufacturer/ OEM	Yes	High
Bill of Materials	Battery manufacturer, OEM, Recyclers	Battery manufacturer / OEM	Yes	High
State of Health	OEM, Recyclers, Transport/ Storage, Second-life technicians	OEM / Battery Management System (BMS) owner	Yes	Medium-high
Maintenance history	OEM, Second-life technicians, Service providers	Service providers / OEM	Yes	Medium-high
Risk of thermal runaway (diagnostics)	Recyclers, Second-life technicians, Transport/ Storage	OEM / BMS owner	Yes	Medium-high
Charging/discharging cycles	OEM, Second-life technicians, Service providers	OEM / BMS owner	Yes	Medium

Data	Actors with Interest in Accessing Data	Relevant Actor for Data Submission	Reluctance	Appetite
Dynamic in-use diagnostics (voltage/ current/impedance)	OEM, Recyclers, Second-life technicians	OEM / BMS owner	Yes	Medium
Environmental performance (e.g., carbon footprint)	Customers, OEM	OEM / Battery manufacturer	Yes	Medium-high
Social performance (due diligence)	Customers, OEM	OEM / Suppliers	Yes	Low
Circularity performance (e.g., recycled content)	OEM	OEM	No	Low
Disassembly instructions / assembly methods	Recyclers, Second-life technicians, Service providers	OEM / Battery manufacturer	No	High
Product design notes for circular economy strategy	OEM, Recyclers, Second-life technicians	OEM	No	Medium
Chain of custody (products/components)	Auditors, OEM, Recyclers, Second-life technicians	OEM	Yes	Medium
Value chain actor name & identifier	Auditors, Customers, OEM	OEM	Yes	Medium
Location of value-adding activity	Auditors, OEM	OEM/Suppliers	Yes	Medium

Reluctance to share data stems from concerns such as competitive risk, exposure of sensitive information, processing complexity, poorly documented and non-standardised information, and low incentives. Where security, privacy and levelled access are key concerns, implementing provably robust cybersecurity measures can increase trust and data submission, thus improving the DPP's value added to stakeholders [3].

Challenges like data verification, standardisation gaps, and immature calculation methods (e.g., State of Health (SoH), Life Cycle Assessment (LCA)), on the other hand, can be addressed by implementing AI, as Machine Learning (ML) models can be used to automate and augment these processes, as seen throughout the various AI use cases discussed in Section 5. The use of AI could, therefore, improve actor contribution to the DPP, allowing for both reliable calculations of required metrics as well as enabling more advanced benefits of the DPP, such as fraud detection. However, adoption will depend on actors' understanding of AI and confidence in its reliability, particularly among less technologically advanced stakeholders. Integrating strong cybersecurity frameworks with AI-driven data extraction, validation, and metric calculation can therefore improve data availability, enhance trust, and maximise DPP impact.

A significant barrier to DPP implementation is the reluctance to share sensitive data due to concerns over intellectual property protection and competitive advantage. Companies are hesitant to disclose proprietary information, such as battery composition or manufacturing processes, without assurances of confidentiality. Non-disclosure agreements are commonly used, but fostering trust across supply chain actors remains challenging, particularly in a competitive market. The lack of trust is compounded by limited awareness of the DPP's benefits and the upcoming EU battery regulation requirements [4].

4. System Architecture & Access Control

The Battery Pass Consortium Report [5] proposes a principal system architecture for DPPs, as depicted in Figure 2. This design highlights three key groups; European Commission (EC) central services, distributed DPP system services, and third-party services.

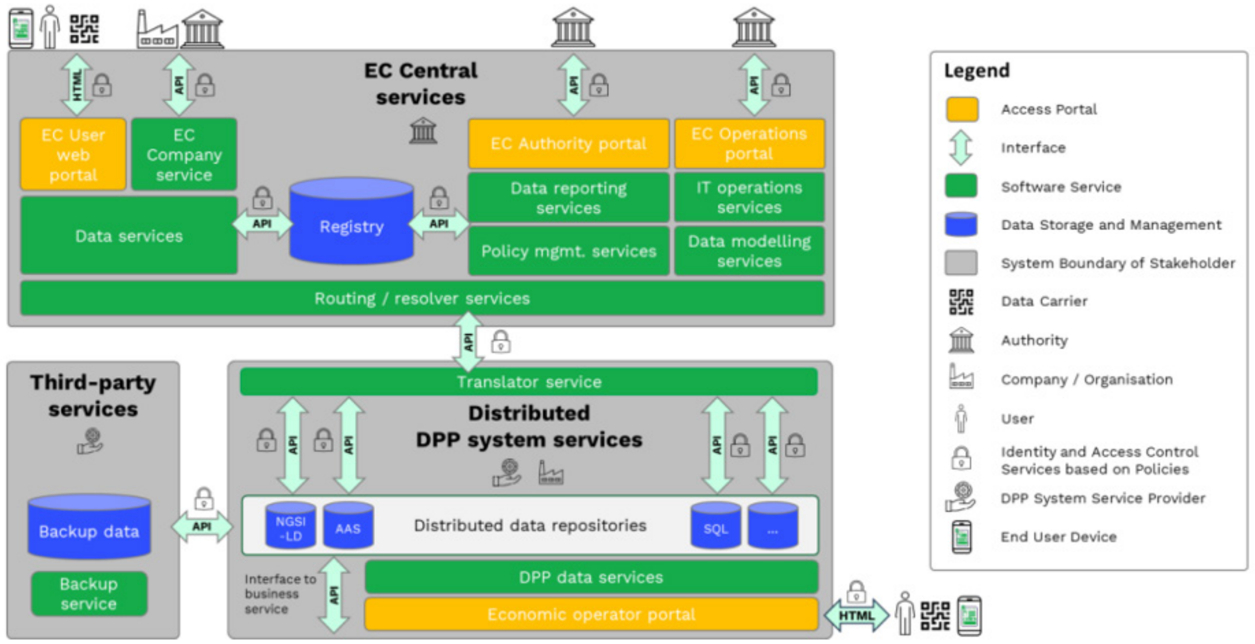


Figure 2: Principal system architecture as proposed in the Battery Pass Consortium report [5].

At the core are the EC Central Services, managed by the European Commission, which act as the backbone of the system. These services provide a centralised registry, enforce sector-specific policies, and maintain a unified governance framework. Their responsibilities include secure provisioning of DPP data to stakeholders such as regulators, manufacturers, and consumers. The second layer consists of Distributed DPP System Services, operated by economic actors such as battery manufacturers or designated service providers. These services manage DPP data and translation functions. Their distributed nature ensures resilience, interoperability, and data integrity, reducing dependency on a single point of control. The third layer comprises Third-Party Services, delivered by external service providers. These services handle specialised functions such as data validation, authentication, and backups. This additional layer enhances scalability and security by segregating critical operations and mitigating risks of system failure.

This architecture ensures trust through centralised governance by the EC Central Services, which enforce compliance and standardisation. Distributed services provide resilience and prevent single points of failure, while third-party services add redundancy and specialised security functions. Approaches such as Distributed Ledger Technology (DLT) or Data Spaces are often recommended for transparency, immutability, and tamper resistance. Furthermore, future integration of AI could support automation and anomaly detection, strengthening both security and operational efficiency.

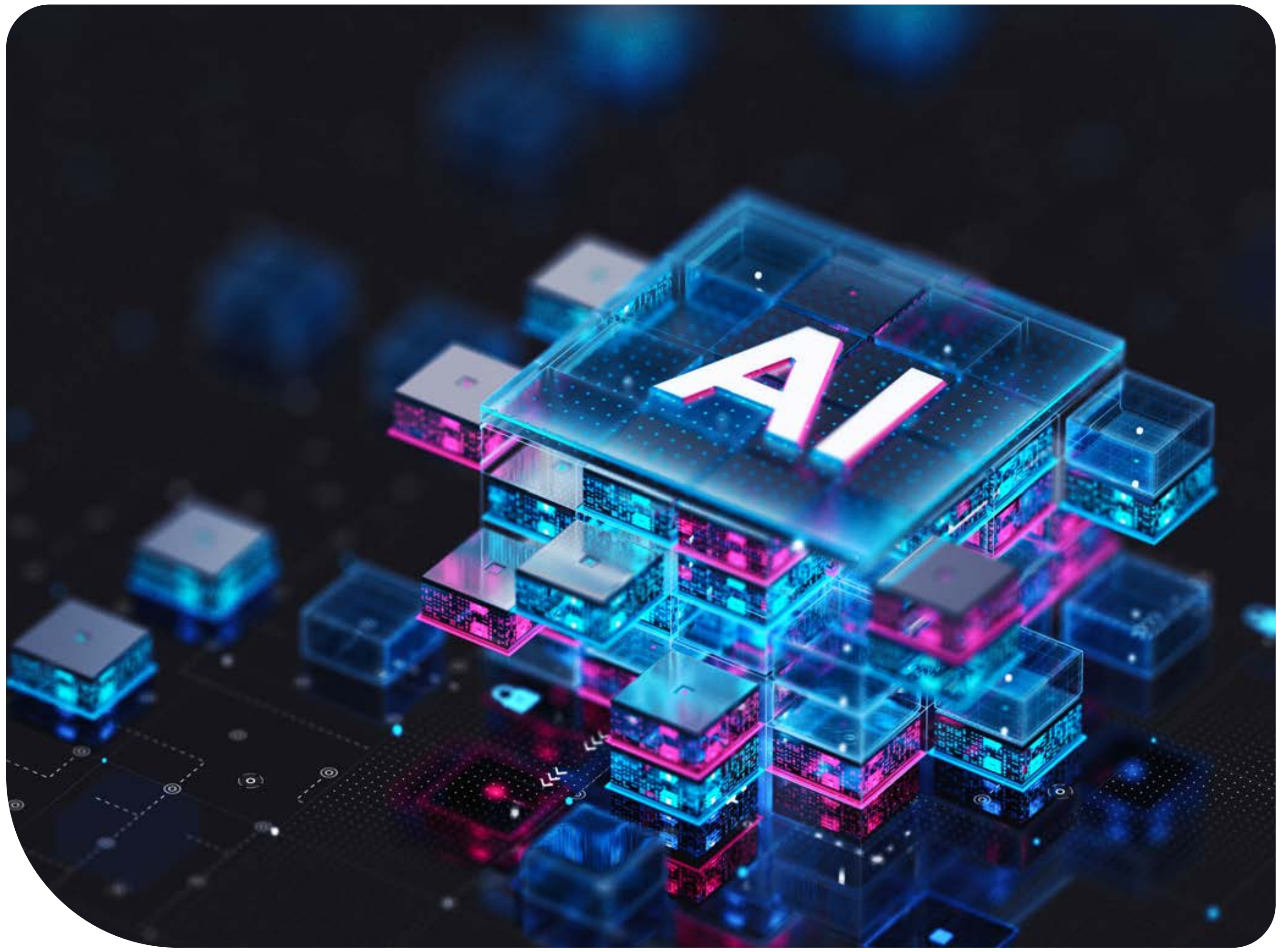
Access to DPP data is controlled through role-based permissions, where stakeholders receive access according to predefined roles. EC Central Services manage secure data distribution, while economic operators handle local data under common standards. Authentication and validation are supported by third-party providers to ensure that only authorised entities interact with the system. To maintain security and compliance, the system should implement role-based access control and identity verification. Audit trails are essential for transparency and regulatory adherence. DLT can provide immutable records of access and changes, while multi-factor authentication and encryption should be applied to secure data exchange.

5. AI Applications & Use Cases

AI, particularly ML, could play a pivotal role in enhancing DPP functionality, as is already starting to be the case on some platforms [6]. AI can be used in data analysis, predictive models, and can support integration into existing systems, both helping reach regulatory compliance and unlocking additional strategic value from DPPs [7]. For instance, AI can analyse large datasets to identify trends, such as supply chain inefficiencies, and provide actionable insights for stakeholders [3].

However, the application of AI in BDPs and other DPPs is still an emerging field. The variety of use cases (e.g., battery health predictions, lifecycle tracking) requires assessing AI technologies on their current benefits and limitations. Developing and integrating these applications will likely demand substantial investment in data infrastructure (for storing battery data and training models) and interoperability, especially for scenarios involving other systems and diverse data formats, such as quality control [8].

Available information on AI for DPPs, however, is limited, with little information on the potential use cases, no guidance on data and methodology requirements, and limited indications of actor interest, thus providing limited benefit to DPP developers. To have a better understanding of the benefits and demand of AI in DPPs an exploration is therefore beneficial.



How to Read This Section:

Each use case is broken down into the following subheadings:

Title

The Use Case
Aims, needs and/or opportunities addressed and summary of high-level approach.

Key Actors of Interest
Actors who benefit most from the use case.

Potential Benefits
Expected value and impact.

Challenges
Main technical and AI-related challenges.

Current Approaches
Common methods and practices, either in the research phase or that are already being tested and implemented.

The objective is not to provide detailed technical solutions but to help DPP developers identify and prioritise use cases by indicating:

- Relevance and demand – via actors, use case and appetite.
- Value added – via potential benefits.
- Effort & implementation complexity – via challenges and current approaches.

This structure enables developers to make informed, strategic based on real industrial impact and benefits.

Health Status & Predictive Health

The Use Case

- Estimating **health metrics** such as SoH, State of Charge (SoC), State of Certified Energy (SoCE) and Remaining Useful Life (RUL) for **monitoring of battery degradation.**
- **Using AI** to analyse sensor logs, battery images and metadata to **achieve higher accuracies** than using traditional methods (such as from the BMS).
- **Overcome limitations of traditional estimation methods** by using AI to incorporate multiple internal and external factors.
- **Leveraging** the centralised access to multiple sources of data throughout battery lifecycle.

Key Actors of Interest

- **EU Committee** – require SoCE to be included in the passport.
- **OEMs** – overcoming the challenge of processing the large volumes of data which they are responsible for submitting.
- **Second-life technicians** – require SoH for assessing second-life suitability and determining the downsizing application.
- **End-of-life technicians** – require SoH for safety precautions before dismantling and for determining the battery's next stage (recycle, refurbish, repair, repurpose).
- **Maintenance technicians** – require SoH for diagnostics and for predictive maintenance.
- **Users** – viewing state of health before purchasing.

Potential benefits

- **Extending battery life** through early detection of anomalies and degradation through comprehensive analysis, allowing early intervention, improving OEM reputation.
- **Lifecycle forecasting** by using RUL to plan for maintenance, replacement or repurposing of battery.
- **Reduced battery waste and associated waste-management costs** which are to be imposed on EVB manufacturers as of 2025, through extended producer responsibility and enablement of circularity.
- **Enabling further functions** of interest on the BDP platform, such as predictive maintenance and adapted disassembly by having access to these metrics.

Challenges

- **Training data** – health metrics are all part of a complex system involving many factors, such as physical degradation, internal resistance, temperature and battery chemistry. Accurate estimations will require extensive training data, which may be locked behind BMS/OEM tools.
- **Computational Intensity** – real-time processing for estimating SoC and SoH, at high accuracies, can be computationally intensive, which can be a risk for causing bottlenecks.
- **Scalability** – securing and maintaining the resources, infrastructures and machine interoperability required for consistent handling and processing of such large amounts of data, for potentially hundreds of thousands of batteries may be challenging and costly.
- **Data quality** – lack of testing standardisation, different sensor resolutions and degradation of sensors, may affect data quality and data processing required.
- **Data availability** – OEMs may be reluctant to share BMS data due to IP and competitive concerns.

Current Approaches

- Data-driven ML models for signal processing of voltage, temperature, capacity and current from charge-discharge cycle data to detect anomalies and find degradation patterns.
- Combining data-driven analysis with physics-informed models based on electrochemical relationships to identify anomalies and degradation patterns.
- Combining data-driven analysis with computer vision to detect physical damage.
- Data-driven ML models for identifying relationships between historical health and usage data, environmental conditions, failure thresholds, physical degradation (if available) and SoH, SoC.
- Data-driven predictive ML models to infer RUL based on SoH, SoC and identified degradation patterns.

Data Extraction & Validation

The Use Case

- Using AI to **extract relevant data from attachments uploaded by users** in various formats (such as PDF documents, images of hand-written notes).
- Use of Large Language Models (LLM) to **automate the 'Extract, Transform and Load' pipeline** to populate the BDP fields.
- Ensuring extracted data is converted **into accepted datatypes** in accordance with the relevant data fields.
- **Validating extracted data and completion of required documents** against trusted sources, such as supplier data.
- Addresses the time-consuming and error-prone process of manual completion/extraction and validation and the need for scalability.

Key Actors of Interest

- **EU Committee** – reduce document-validation time by having pre-checked documents.
- **Technicians across value chain** – easier use as they will have more flexibility on the document type they can upload and will not have to manually fill in forms on the BDP platform, potentially duplicating work.
- **OEMs** – ensure all data and documentation is to the correct standards to avoid failing quality checks and conformity audits run by the EU committee; addresses apprehension around standardising documentation.

Potential benefits

- **Improve data quality and abundance** by positively influencing actors across the value chain who may have been reluctant to fill in BDP fields directly.
- **Carry out pre-EU-audit checks** to avoid failing the audit and having to spend additional time amending the passport, or having the approval withdrawn or suspended.
- **Reduced operational costs** related to document standardisations and verification, data cleaning and compliance checks.

Challenges

- **Lack of standardisation** across companies in document structures, languages and schemas, requiring more complex models to identify relevant information.
- **Processing** different handwritings may be difficult and could introduce errors. Further cross-validation may be needed which may increase computational intensity.
- **Computational intensity and associated costs** – training and inference of LLMs requires high computational power and data storage, increasing the overall cost for running the passport.
- **Data privacy and security** of sensitive data and protecting against data breaches or model inversion attacks.

Current Approaches

- Optical Character Recognition for capturing text content in image files (e.g: PDFs, photos)
- Natural Language Processing (NLP) and Named Entity Recognition for classifying documents based on type of content identified and extracting relevant information.
- ML validation models to detect anomalies, such as inconsistent carbon footprint values or mismatched supplier IDs.
- Using Robotic Process Automation (software robots which automate repetitive 'office tasks') for routing documents for approval, updating databases and trigger follow-up actions.
- Vision Language Models for visual and text processing, particularly where visual positioning (e.g., checkboxes) is crucial.

End-of-Life Management

The Use Case

- **Determining a battery's optimal end-of-life sentencing**
- Using AI to analyse degradation patterns from data such as health metrics, maintenance history, images and sensor test data, as well as chemical composition for **transparent, standardised sentencing.**
- Addressing the limitations of manual end-of-life sentencing, particularly for second-life opportunities, by accounting for the complex degradation mechanism and safety risks associated with the different sentences.

Key Actors of Interest

- **End-of-life technicians** – support in making informed and reliable decisions while taking into account the many factors at play.
- **EU committee** – have emphasised the role of BDPs in facilitating the preparation for end-of-life processes.

Potential benefits

- **Increased uptake of repurposing, remanufacturing and repairing of batteries** enabled by overcoming the difficulties in assessing a battery's state at end-of-life (EoL) through traditional methods.
- **Increased circularity, reducing reliance on virgin raw materials** and associated ESG and supply risks.
- **Enabling further functions** such as insights for design and battery chemistry improvements.
- **Prepare for anticipated future EU Regulations** on end-of-life management emphasis on alternative routes.
- **Maximising value of data** made available, and other AI-obtained metrics.

Challenges

- **Data availability** – incomplete data, either due to reluctancy of OEMs to share data, poor information transfer, or neglect due to actors' lack of awareness of importance of said data.
- **Data fusion** – determining EoL sentencing relies on many factors, some of which are obtained directly from actors, others from sensors and others from calculated/predicted metrics, introducing more risks to inaccurate results.
- **Transparency and explainability** – due to high stakes associated with incorrectly sentencing a battery at EoL, stakeholders will likely require explanations to how decisions were made and the associated risk level to be able to adopt it. Due to the 'blackbox' nature of many ML methods, this may prove difficult.
- **Computational intensity and associated costs** – analysing usage/maintenance history and images may require computationally intensive AI such as LLMs, for which training and inference requires high computational power and data storage. This will likely increase the overall cost for running the passport.

Current Approaches

- Data-driven ML models for signal processing of voltage, temperature, capacity and current from charge-discharge cycle data to detect anomalies and degradation patterns.
- Computer vision of battery images to detect and classify degradation and physical damage.
- LLMs to analyse historical maintenance logs and extract relevant information.
- Combining data-driven analysis with physics-informed models based on electrochemical relationships to predict failure modes.
- Data-driven ML models for identifying relationships between historical health and usage data, environmental conditions, failure thresholds, physical degradation and EoL sentencing.

Supply Chain Due Diligence Compliancy

The Use Case

- Identifying and flagging high-risk suppliers breaching EU Due Diligence guidelines.
- **Using AI to assign risk levels to suppliers by processing publicly available data** such as satellite imagery, world event databases, political instability, trade flows, audits and environmental reports.
- Meeting the EU Regulations Due Diligence requirement to include a management system for responsible sourcing – including both environmental and social aspects.
- Providing OEMs with information on the ESG risks, and political picture of, suppliers throughout the value chain, which is often missing or difficult to obtain directly from suppliers.

Key Actors of Interest

- **OEMs** – work towards meeting EU Regulations requirements and improve transparency of their end-to-end value chain in a reliable and cost-effective manner.
- **Members of the public** – due diligence reports will be accessible to the wider public. As ethical consumerism in on the rise, such information is likely to increasingly be of interest to consumers and to influence purchasing decisions.
- **EU committee** – although not a direct requirement in the EU Regulation for due diligence managements systems to be embedded within the BDP, OEMs must be able to evidence that there is one in place and must pass third party audits carried out by appointed assessment bodies – with bodies and specific guidelines yet to be specified. [9]

Potential benefits

- Reduced reliance on suppliers for obtaining self-reported ESG data, and so reduced risk of unexpectedly failing third-party audits due to withheld data.
- Supports the creation of a management system for responsible sourcing, as required by the EU Battery Regulation and Corporate Sustainability Due Diligence Directive.
- Improved supply resilience due to early detection of emerging risks before escalation.
- Improved reputation by demonstrating commitment to ethical and sustainable practiced.

Challenges

- **Data availability** – incomplete data, either due to reluctancy of OEMs to share data, poor information transfer, or neglect due to actors' lack of awareness of importance of said data.
- **Data quality** – databases and satellite images may not be regularly updated, and verification of reports on events may take time, thus hindering the real-time relevance. Input data from suppliers may also not be accurate, such as vague locations, particularly for raw material mining and processing.
- **Managing bias** – bias may creep into the model if data sources' credibility and neutrality are not properly assessed, and if data processed is limited to certain languages or countries of origin.
- **Computational intensity and associated costs** – processing large amounts of data, including text – possibly from different languages – and images, for inference and training is computationally expensive.
- **Transparency and explainability** – decisions must be transparent and auditable to meet EU AI Act and Battery Regulations requirements.

Current Approaches

- NLP for processing reports, audits, news articles, trade flow data, research journals and other relevant sources; and identifying and classifying mentions of ESG risk-related issues.
- Computer vision and geospatial AI for analysing satellite imagery to detect deforestation, conflict zones and illegal land use to map ESG risks geographically across supplier regions.
- ML risk model to process NLP and computer vision model outcomes, weigh feature importances and effect on supply availability, and provide final scores.

Carbon Footprint Calculation & Validation

The Use Case

- **Using AI to improve accuracy of carbon footprint estimates** by analysing a wide range of inputs across the battery's lifecycle (excluding the use phase, as per EU Regulations), focusing on raw material extraction, processing, manufacturing and recycling.
- Flagging inconsistencies or anomalies in reported emissions data and raising these to OEMs.
- Enabling battery-specific footprint calculation, rather than relying on generic averages, for a more precise and transparent view of environmental impact.

Key Actors of Interest

- **OEMs** – required to submit carbon footprint declarations under EU battery regulations.
- **Members of the public** – increasingly interested in ethical and sustainable consumerism and reducing their own environmental impacts.
- **EU committee** – responsible for verifying carbon footprint data and ensuring compliance.

Potential benefits

- Improved accuracy and transparency of carbon declarations, enhancing trust and regulatory compliance.
- Enables lifecycle-based sustainability insights, useful for product innovation and selecting suppliers.
- May reduce audit failure risk by providing verifiable, data-driven estimates, and by flagging anomalies so OEMs can follow up with relevant suppliers to gain accurate data.

Challenges

- **Data availability** – carbon data is often incomplete, inconsistent or proprietary, and actors may be reluctant to provide information.
- **Data quality** – lack of standardised formats for carbon data across manufacturers and suppliers, as well as variability in how emissions are calculated depending on the emission scope, may impact performance and accuracy of the AI model and estimations.
- **Transparency and explainability** – decisions must be transparent and auditable to meet EU AI Act and Battery Regulations requirements, and estimations must be traceable to real-word data.
- **Failing audits due to over-generalisation of estimations** – some available solutions extensively, or even solely, rely on LLM-generated estimations. Using LLMs to fill missing gaps can be useful but should not be used as replacement for obtaining data from actors throughout the supply chain. Failing to prove explainable, evidence-backed values can lead to failing audits and risk the BDP being withdrawn.

Current Approaches

- NLP for extracting emissions data from sustainability reports, audits, certificates and other relevant documentation.
- Anomaly detection models for identifying and flagging unlikely values by comparing to existing supplier information and values from similar contexts.

Quality Control

The Use Case

- Using AI for quality control of disassembled and re-assembled battery parts ready for a second life.
- Processing and analysing inspection and testing data and cross-referencing with battery model technical data and Computer-Aided Design (CAD) models to identify defects.
- Identifying and classifying battery defects based on their severity, alerting the user on severity and location, and suggesting the resulting sentencing, such as 'pass', 'fail', or 'rework'.
- Logging defects and sentences to the BDP.

Key Actors of Interest

- **OEMs** – assurance of battery quality, safety and compliance with regulations.
- **Second-life technicians** – support in basing decisions on the correct model, and making informed, evidence-backed and reliable decisions.
- **EU committee** – intent on digital passports being a means to contribute and develop the circular economy.

Potential benefits

- **Minimise human error and risk of defective batteries reaching the market,** as waste management operators may struggle to detect model-specific defects amongst thousands of different models.
- Standardising quality control across diverse battery types and conditions.
- **Supporting circular economy goals** by enabling safe reuse and reducing waste, thus reducing reliance on raw materials and supporting OEMs in their responsibility towards waste management.
- **Reducing part recalls and system downtime** through early fault detection.

Challenges

- **Data quality** – consistency in lighting and resolutions for image-processing, and in sensor data and format from different machines and suppliers, may be difficult to obtain.
- **Data availability** – actors may not be willing to connect their vision systems with BDP due to security reasons, and technicians may not prioritise uploading photos (particularly if many angles are required).
- **Training data availability** – large, labelled datasets required for image processing deep learning models may be difficult and time-consuming to obtain.
- **Transparency, explainability and trust** – decisions must be transparent and auditable to meet EU AI Act and Battery Regulations requirements, and must be trusted by technicians, which can be difficult for black box AI models.
- **Computational intensity and associated costs** – rising operational costs required for meeting the high computational power and data storage demands for training and inference of AI on large, and accumulation of model-specific data

Current Approaches

- Data-driven ML models for signal processing of voltage, temperature, capacity and current from testing data to detect anomalies and find degradation patterns.
- Computer vision of battery images to detect cracks, misalignments or cracks and comparing real-time images with CAD models to identify defects.
- ML models to classify defects by severity and alert technicians with location and recommended actions.
- LLMs to analyse historical maintenance logs and extract relevant information.
- Data-driven ML models for identifying relationships between historical health, usage data, environmental conditions, physical degradation and sentencing outcome.

Adaptive Disassembly

The Use Case

- Using AI to generate tailored disassembly instructions based on the battery's specific condition, history, and configuration.
- Analysing data from the battery passport – such as battery chemistry, maintenance history, and step-by-step instructions and information on tools, fasteners and precautions – to adapt disassembly procedures.
- Supporting technicians by highlighting risks, suggesting tools, and flagging components that may be fragile, hazardous, or non-standard.
- Addressing the lack of tailored guidance for technicians' handlings diverse battery types.
- Addressing the lack of standardised documentation

Key Actors of Interest

- **Service providers/Second-life technicians** – require tailored instructions to safely and efficiently disassemble batteries for reuse or refurbishment and may not have time or specialist knowledge to interpret long battery history logs to draw actionable insights.
- **EU Committee** – interested in promoting circularity and safe handling of batteries. Further develops on the information required by EU Regulations on dismantling of batteries.
- **OEMs** – are required to submit disassembly data but have concerns around poor documentation and lack of standardisation.

Potential benefits

- **Improved Safety** – AI can flag hazardous components or damaged areas, reducing risks to technicians and potential accidents.
- **Improved operational efficiency** – tailored instructions reduce trial-and-error in the disassembly process and reading of lengthy battery history records.
- **Enhanced circularity** – tailored instructions enable components to be disassembled without causing damage, enabling more components to be reused or repurposed.
- Supports and builds on the EU Regulations requirements to include disassembly instructions, any necessary precautions and any risk of damaging parts if dismantled.

Challenges

- **Data quality** – obtaining the extensive data – including fastener type, instructions, damage and maintenance history – for model training and generating accurate results may be limited due to OEM and technician negligence or reluctance.
- **Transparency, explainability and trust** – decisions must be transparent and auditable to meet EU AI Act and Battery Regulations requirements, and must be trusted by technicians, which can be difficult for black box AI models.
- **Real-time processing constraints** – generating instructions on-demand may require edge computing or fast cloud access, which may not be affordable or logistically possible for the relevant actors.
- **Computational intensity and associated costs** – analysing images and text will require the use of LLMs, for which training and inference requires high computational power and data storage. This will likely increase the overall cost for running the passport. Storage needs will also increase as model-specific data accumulates.

Current Approaches

- LLMs to interpret manufacturer manuals, maintenance logs and available text data in the BDP, and to generate final instructions.
- Computer vision to detect corrosion, swelling or damage.
- ML models for signal processing from temperature, voltage, current and capacitance test data.
- ML models for estimating residual energy and thermal risks, based on sensor and historical data.
- ML models to analyse defect type and determine risks and effects on handling and dismantling, using historical data.

Fraud Detection

The Use Case

- **Using AI to detect and flag fraudulent activity within BDPs**, such as tampered data, forged documentation and inconsistencies suggesting potential counterfeit parts.
- Cross-referencing BDP input data and sensor data with expected and learnt battery model-specific data to identify anomalies and potential fraud or counterfeit parts.
- Using blockchain and AI to analyse transactions.
- **Meeting EU Regulations** mandating traceability and authenticity of battery data.
- **Addressing the rise in circulation of counterfeit and fraudulent battery parts**, compromising safety and performance.

Key Actors of Interest

- **OEMs** – avoiding reputational damage by avoiding battery accidents due to counterfeit parts being wrongly associated with them.
- **EU Committee** – tasked with verifying compliance and preventing fraudulent entries.
- Second-life technicians – rely on accurate data to assess battery suitability, safety and sentence.
- **Notified bodies** – involved in audits and conformity assessments.
- **Users** – increased trust in second-life parts market.

Potential benefits

- Reducing risks of accidents and regulatory violations by preventing counterfeit or tampered batteries from entering the market.
- Reduces costs associated with warranty fraud and liability costs.
- Ensures authenticity of BDP data, supporting regulatory compliance.
- Improved trust in second life and recycled batteries, supporting EU circular economy goals.

Challenges

- **Data availability** – fraud detection relies on access to comprehensive data throughout a battery's lifecycle, which may be incomplete, withheld by specific actors or in inaccessible file formats.
- **Data quality** – inconsistent documentation format and differences in sensor calibrations, sensitivities and resolutions may hinder anomaly detection.
- **External-dependencies** – poor network connectivity or latency in data transmission, as well as potentially long processing time, may limit rapidity of fraud detection and alerting, resulting in fraudulent batteries entering the market, which may reduce the reliability of the feature.

Current Approaches

- Data extraction models for obtaining textual data from reports.
- LLMs for detecting inconsistencies in textual/written documentation.
- ML models for signal processing of sensor data and cross-referencing with expected model-specific patterns to detect anomalies or inconsistencies.

6. Summary & Conclusions

DPPs should not be treated as a mere compliance exercise. While regulatory requirements make their implementation inevitable, businesses that embrace DPPs strategically can unlock significant value far beyond compliance. Rather than viewing DPPs as a box-ticking obligation, organisations can leverage them to differentiate products, build customer loyalty, and gain a competitive edge.

Key value drivers beyond compliance:

- Improved supply chain management through enhanced transparency and traceability.
- Opportunities for environmental impact reduction, supporting sustainability goals.
- Better risk management by mitigating supply chain and reputational risks.
- Product innovation opportunities, enabling new services and circular business models.
- Increased product value and potential for resale, repair, and leasing markets.
- Consumer trust and brand reputation, driven by verified product data.
- Counterfeit prevention, ensuring authenticity and protecting brand integrity.
- Driving sustainability and circular economy, aligning with global ESG commitments.

The implementation of DPPs is an inevitable development within contemporary regulatory frameworks. Organisations face a strategic decision: to adopt DPPs merely as a compliance mechanism or to leverage their transformative potential to generate added value, enhance customer engagement, and ensure long-term organisational resilience.

7. Key Takeaways

Key takeaways:

- **DPPs are a strategic value platform, not a box-ticking exercise.** Done right, they drive product differentiation, build customer trust, enable circular models, and deter counterfeits.
- **Early DPP adoption offers advantage.** Integrating DPPs ahead of deadlines reduces last-minute risks and penalties, improves internal audits, and positions adopters as leaders in sustainability and innovation.
- **Actor dynamics matter.** Different value chain actors have varying appetites and reluctance to share data. Addressing IP/privacy concerns and standardisation gaps is essential to improve data availability and quality.
- **AI is a key enabler across the passport lifecycle.** It converts fragmented lifecycle data into secure, auditable insights, scaling DPPs and unlocking value beyond compliance.
- **Security drives participation.** Robust cybersecurity and levelled access increase trust and reduce reluctance to share sensitive data.

8. References

1. M. Ackermann, August 2025. [Online]. Available: https://info.link/en/resources/eu-digital-product-passport-requirements-benefits-and-implementation.
2. European Parliament and the Council of the European Union, “Regulation (EU) 2023/1542 of the European Parliament and of the Council,” Official Journal of the European Union, 2023.
3. K. Berger, R. J. Baumgartner, M. Weinzerl, J. Bachler, K. Preston and J.-P. Schöggl, “Data requirements and availabilities for a digital battery passport – A value chain actor perspective,” 2023. [Online]. Available: https://doi.org/10.1016/j.clpl.2023.100032. [Accessed 30 June 2025].
4. V. Rizos and P. Urban, “IMPLEMENTING THE EU DIGITAL BATTERY PASSPORT,” 2024. [Online]. Available: https://cdn.ceps.eu/wp-content/uploads/2024/03/1qp5rxiZ-CEPS-InDepthAnalysis-2024-05_Implementing-the-EU-digital-battery-passport.pdf. [Accessed 06 July 2025].
5. SYSTEMIQ, “Battery Passport Technical Guidance - Technical challenges, standards and recommondations for a battery passport system,” 2024. [Online]. Available: https://www.systemiq.earth/wp-content/uploads/2024/03/2024_BatteryPassport_Technical_Guidance.pdf. [Accessed 06 July 2025].
6. Electra, “Electra Introduces EVE-AI - EAGLE Battery Pass,” [Online]. Available: https://www.electravehicles.com/electra-introduces-eve-ai-eagle-battery-pass/. [Accessed 09 12 2025].
7. S. Patel, “The AI advantage: get ready for battery passports,” 2024. [Online]. Available: https://www.automotiveworld.com/articles/the-ai-advantage-get-ready-for-battery-passports/[](https://www.automotiveworld.com/articles/the-ai-advantage-get-ready-for-battery-passports/). [Accessed 30 June 2025].
8. Fraunhofer-Gesellschaft, “Circular economy: A digital EU product passport for batteries,” 2024. [Online]. Available: https://www.fraunhofer.de/en/press/research-news/2024/april-2024/circular-economy-a-digital-eu-product-passport-for-batteries.html. [Accessed 30 June 2025].
9. European Union and Council of the European Union, “Regulation of the European Union and of the Council amending Regulation (EU) 2023/1542 as regards obligations of economic operators concerning battery due diligence policies,” 2025. [Online]. Available: https://data.consilium.europa.eu/doc/document/PE-28-2025-INIT/en/pdf.

Appendix

Table 3: Minimum required data by the EU Regulations and actor access to data [2].

Data	Actors			
	Member of the Public	Person with Legitimate Interest	The Commission	Notified Bodies, Market Surveillance Authorities
Manufacturer	Y			
Battery category	Y			
Place of manufacture	Y			
Date of manufacture (M/Y)	Y			
Weight	Y			
Capacity	Y			
Chemistry	Y			
Hazardous substances	Y			
Usable extinguishing agent	Y			
Critical raw materials	Y			
Material composition	Y			
Carbon footprint	Y			
Info on responsible sourcing	Y			
Recycled content	Y			
Share of renewable content	Y			
Rated capacity (Ah)	Y			
Minimal, nominal and maximum voltage	Y			
Original power capability (W) and limits	Y			
Expected battery lifetime, in cycles	Y			
Capacity threshold for exhaustion	Y			
Withstand temperature swings when not in use	Y			
Warranty period	Y			

Data	Actors Member of the Public	Person with Legitimate Interest	The Commission	Notified Bodies, Market Surveillance Authorities
Initial round trip energy efficiency at 50% of life cycle	Y			
Internal battery cell and pack resistance	Y			
C-rate of cycle-life test	Y			
Marking requirements	Y			
EU declaration of conformity	Y			
Info on prevention and management of battery waste	Y			
Detailed composition incl. Materials in cathode, anode & electrolyte		Y	Y	
Part numbers for components and contact details for replacement spares		Y	Y	
Exploded diagrams of battery system/pack		Y	Y	
Disassembly sequences		Y	Y	
Type and number of fastening techniques		Y	Y	
Tools required for disassembly		Y	Y	
Warning if risk of damaging parts exist		Y	Y	
Number of cells used and layout		Y	Y	
Safety measures		Y	Y	
Results of test reports proving compliance with regulations			Y	Y
Values for performance and durability parameters when battery placed on the market and when subject to changes in its status		Y		
State of Certified Energy (EV)		Y		
Information on battery status (e.g.: original, repurposed, re-used, etc...)		Y		

Data	Actors Member of the Public	Person with Legitimate Interest	The Commission	Notified Bodies, Market Surveillance Authorities
Historical data on number of charging and discharging cycles		Y		
Historical data on negative events (e.g.: accidents)		Y		
Periodically recorded information on operating conditions (e.g.: temperature and state of charge)		Y		
Applied discharge and charge rate		Y		
Ratio between nominal battery power (W) and battery energy (Wh)		Y		
Depth of discharge in the cycle-life test		Y		
Power capability at 80% and 20% SoC		Y		
Any calculations performed		Y		

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